Journal of Behavioral and Experimental Economics 63 (2016) 22–35

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Economics

journal homepage: www.elsevier.com/locate/socec

Over-the-counter markets vs. double auctions: A comparative experimental study☆

Giuseppe Attanasi[a,*], Samuele Centorrino[b], Ivan Moscati[c]

[a] BETA, University of Strasbourg, 61 Avenue de la Forêt-Noire, Strasbourg, 67085 Cedex, France
[b] Economics Department, Stony Brook University, Social and Behavioral Sciences Building, Stony Brook, NY 11794, United States
[c] Department of Economics, University of Insubria, Via Monte Generoso 71, Varese 21100, Italy

ARTICLE INFO

Article history:
Received 19 March 2015
Revised 14 March 2016
Accepted 14 March 2016
Available online 6 April 2016

JEL Classification:
C92
D41
D47

Keywords:
Market experiments
Over-the-counter market
Double auction
Private vs. public information
Efficiency

ABSTRACT

We study an electronic over-the-counter (OTC) market, in which each agent looks for the best counterpart through bilateral negotiations. We compare its performance with the standard electronic double-auction (DA) market, in which traders post their quotes publicly. We show that the lack of information in the OTC market induces an efficiency loss, characterized by an average closing price below the competitive price and by a traded quantity below the competitive quantity. We further test the robustness of these findings when exogenous shocks modify the competitive equilibrium. Among other things, we show that supply shocks increasing the competitive quantity improve OTC's efficiency.

1. Introduction

Over-the-counter (OTC) markets are decentralized trading mechanisms in which each trader looks for the best counterpart through private, and typically bilateral, negotiations. There exist many types of OTC markets, which differ in features such as the exact process through which each trader searches for a counterpart, the possible presence of intermediating traders such as brokers, or the nature of the traded commodity. There are, however, two main features characterizing all OTC markets. First, traders are price makers, and different buyers and sellers (typically) trade the same commodity at different prices. Therefore, OTC markets are not competitive markets. Second, OTC traders have less information than traders operating in other non-competitive but more centralized markets, such as auction markets. More precisely, while in auctions potential buyers and sellers are made aware of the trade opportunities available in the market – be it by an auctioneer, an easily accessible order book, or some other market institution – this does not happen in OTC markets. As Duffie (2012, p. 1) aptly remarks, OTC traders are "somewhat in the dark about the most attractive available terms and about whom to contact for attractive terms." This lack of public information influences the functioning of OTC markets and, as we will argue, makes them less efficient than more centralized trading mechanisms such as auctions.

OTC markets are economically relevant because many assets – such as government and corporate bonds, derivatives, currencies, real estate, and bulk commodities – are often traded on a private, bilateral basis. Despite their importance, however, the study of OTC mechanisms is "still underdeveloped in comparison to the available research on central market mechanisms" (Duffie, 2012, p. xiii).

☆ This paper has been circulated previously under the title "Double Auction Equilibrium and Efficiency in an Experimental Search Market". The authors would like to thank Olivier Armantier, Antonio Bisignano, Fortuna Casoria, Andrea Guido, Luigi Luini, Joshua Benjamin Miller, Camilla Peroni, Gabriella Punzi, Valentina Rotondi, Viola Saredi, and participants in the 2011 Labsi Conference, Capua, Italy, the 2012 Annual Xiamen University International Workshop on Experimental Economics and Finance, Xiamen, China, the 2013 Storep Conference, Gaeta, Italy, and the SIE 2013 Conference, Bologna, Italy, for useful comments and remarks. G. Attanasi gratefully acknowledges financial support by the Foundation for an Industrial Safety Culture (Fondation pour une Culture de Sécurité Industrielle, FONCSI), by the European Research Council (ERC Starting Grant DU 283953), and by Attractivité IDEX 2013 (University of Strasbourg). Ivan Moscati thanks Fondazione Cariplo for financial support.

* Corresponding author. Tel.: +33659200132.
E-mail addresses: attanasi@unistra.fr (G. Attanasi), samuele.centorrino@stonybrook.edu (S. Centorrino), ivan.moscati@uninsubria.it (I. Moscati).

http://dx.doi.org/10.1016/j.socec.2016.03.003
2214-8043/

In this paper, we contribute to the filling of this gap by studying the functioning of an experimental OTC market that can be seen as an extension of the pit market designed by Chamberlin (1948) in a seminal contribution to the experimental literature on market institutions. We compare its performance to that of a centralized market, namely the well-known experimental double-auction (DA) market introduced by Smith (1962) (for a review of the experimental research on DA markets, see Friedman and Rust, 1993; Plott, 2008; Cason and Friedman, 2008).

Duffie and his co-authors have constructed theoretical models for a number of OTC markets (Duffie, 2010; 2012; Ashcraft and Duffie, 2007; Duffie et al., 2005; 2007; Duffie and Manso, 2007; Duffie et al., 2010a; 2009; 2010b; 2014). We adopt a different but complementary perspective, and study OTC markets experimentally. In particular, our OTC and DA experimental markets are electronic, in the sense that our traders interact only via computer. This allows us to rule out information spillovers that may occur when OTC bargaining is conducted orally. To the best of our knowledge, our paper is the first study of an electronic OTC market from an experimental perspective.[1]

Our OTC and DA experimental markets share some common features (more details in Section 2). In both settings, each experimental session involves 40 subjects who are equally divided into buyers and sellers. Each of the 20 sellers is exogenously assigned one unit of an imaginary homogeneous good, and a valuation indicating the minimum amount he/she has to receive for his/her unit. Each of the 20 buyers is exogenously assigned a valuation indicating the maximum amount he/she can spend for one unit of the good. Each experimental session consists of nine trading periods during which buyers and sellers have to trade the good by posting bid quotes (buyers) or ask quotes (sellers). As already noted, buyers and sellers interact only electronically: they post their quotes using their computer's keyboard, and all the information they receive about what is happening in the market is the information appearing on their computer's screen.

What is different between our OTC and DA experimental markets is the way traders post their quotes, and the information they receive about the quotes posted by other traders in the market. In our DA market, buyers and sellers post their quotes publicly in the sense that each buyer (seller) addresses his/her bids (asks) to all sellers (buyers) in the market, and these quotes are disclosed to all traders in the market by appearing on their screens. Thus in the DA market at each moment each buyer (seller) is informed about the best bid (ask) currently present in the market, but also knows the entire previous history of public bids and asks. This feature of the DA market is called *pre-trade price transparency*. In actual OTC markets, pre-trade price transparency and the relevant public information associated with it are absent. Therefore, in our OTC setting, buyers and sellers post their quotes privately, that is, each trader can make/receive only one electronic quote at a time to/from a single counterpart, and only the sender and the receivers of the quote observe it on their screens. Therefore, in our OTC market each buyer (seller) is informed only about the bids (asks) he/she makes and has made, and about the asks (bids) he/she receives and has received.

In the DA market, when a buyer accepts a public ask, or a seller accepts a public bid, a transaction is enacted, and the closing price appears on the screens of all traders. This market feature is called *post-trade price transparency*. In a number of actual OTC markets, such as those for U.S. corporate and municipal bonds, financial regulators have mandated post-trade price transparency, often implemented through a program called the Trade Reporting and Compliance Engine (TRACE). We impose post-trade price transparency also in our OTC experimental market: when a buyer (seller) accepts an ask (bid) privately made to him/her by a seller (buyer) in the market, the closing price and the identification numbers of the two traders are made public by appearing on the screens of all traders in the market.[2]

In order to study the functioning of our OTC market and compare its efficiency to that of a DA market, we ran a series of classroom experiments. The experiments involved more than 3300 undergraduate students of almost the same age (19 or 20 years old when performing the experiment), nationality (around 80% Italians), and field of study (economics), and were performed over a period of six years, namely from 2009 to 2014, inclusive. Because the exceptionally large number of students involved in our setting would make paying them too expensive, and as is indeed common in many classroom experiments (see Holt, 1996; 1999), we did not use monetary incentives. Rather, we incentivized students to play effectively by publicly praising the best performing traders among them (more details in Section 2).

Our main research hypothesis was that the information disadvantage of the OTC mechanism, where only post-trade price transparency is implemented, with respect to the DA mechanism, where both pre-trade and post-trade transparency are implemented, makes the OTC market less efficient than the DA market. Our experimental findings validate this research hypothesis: our OTC market is less efficient than our DA market. We take as our index of efficiency the ratio between the total surplus actually obtained in the market and the total surplus that could have been obtained if the market were perfectly competitive. We find that, while in DA markets the average efficiency index is about 93 over 100, in OTC markets the efficiency index is about 85 over 100. Thus the information gap between the OTC and the DA settings determines a loss of efficiency of almost 8 efficiency points. We show that changes in subjects' learning and reduction in trading period time do not change this result.[3]

To better understand how the lack of pre-trade price transparency – i.e., the lack of information about the entire history of bids and asks – affects negatively the efficiency of the OTC mechanism, we study the pattern of closing prices and traded quantity in both the OTC and the DA settings. We find that, because of its informational features, in the OTC mechanism closing prices

[1] Holt (1996) provides a description of classroom experiments based on an OTC market where buyer-seller bargaining is conducted orally. Hendershott and Madhavan (2015) study traditional OTC trading based on telephone and voice communications. In particular, they use data on corporate bond trades between 2010 and 2011 to investigate which factors influence the transition from voice-based OTC trading to DA trading based on electronic platforms such as MarketAxess. Among other things, they find that bond liquidity enhances the transition from voice-based OTC to electronic DA.

[2] As mentioned above, if regarded in historical perspective, the design of our DA market follows Smith (1962), while our OTC mechanism takes inspiration from Chamberlin (1948). However, Chamberlin did not always make public the price of closed transactions, while we always implement post-trade price transparency. Furthermore, Chamberlin let experimental subjects trade for one single market period while we follow Smith (1962) and subsequent standard practice in market classroom experiments (see, e.g., Holt, 1996; Cason and Friedman, 2008), and allow experimental subjects to trade for several periods so that they can gain experience about how the trading mechanism works.

[3] Recently, a trading mechanism in the spirit of Chamberlin (1948) has been investigated by List (2002, 2004) in field experiments involving a sports card market and a collector pin market. As in Chamberlin's setting, but differently from ours, in List's experiment the buyer-seller bargaining is conducted orally rather than via computer. Like us and differently from Chamberlin, however, List allows subjects to trade for multiple periods (four), rather than for a single period. One key feature of List's experimental design is that subjects choose endogenously their role as buyers or sellers; by contrast, we follow Chamberlin (1948) and Smith (1962) in assigning subjects to one of the two roles exogenously and randomly. More generally, the focus of List's experiments is to examine how the experience of buyers and sellers influences the outcomes of an OTC market. Our main goal, by contrast, is to compare the performances of an OTC market and a DA market under the assumption that traders have similar market experience.

converge to a price that is below the competitive price. This implies that the traded quantity is lower than the competitive quantity and this, in turn, proves to be the main source of the OTC's inefficiency.

We take the analysis further: we decompose the loss of efficiency associated with both the OTC and DA mechanisms into two main components – intra-marginal inefficiency and extra-marginal inefficiency – and show that, while the inefficiency associated with the DA mechanism is almost completely of the extra-marginal type, the inefficiency of the OTC mechanism is an even mixture of both types. Finally, to deepen our comprehension of the OTC mechanism, we introduce shocks into the picture and study how efficiency in the OTC and the DA mechanisms is affected by different types of shocks, that is, by shifts in either the demand curve or the supply curve that modify the competitive equilibrium. We find that, in the short run, none of these shocks substantially affect the efficiency of either the OTC or the DA mechanism. However, in the long run, a shock that shifts downwards the supply function is able to significantly increase the efficiency of the OTC market only. This is due to a reduction in the difference between the competitive price and the average closing price, this difference usually being positive in the OTC market.

The rest of the paper is organized as follows: in Section 2 we illustrate the experimental design. In Section 3 we outline a simple theoretical model of search under incomplete information and, based on it, make some predictions about the experimental findings. In Section 4 we present our experimental findings. In Section 5 we summarize the paper and discuss some policy implications of our experimental findings.

2. Experimental design

Procedures. We ran computerized classroom experiments through the z-Tree software (Fischbacher, 2007). Sessions were held at Bocconi University, Milan, during a first-year introductory course in Microeconomics over six consecutive academic years, from 2009 to 2014.[4] All classroom experiments were held in the month of October (first semester), always in the same computerized room, and run by the same experimenter (G. Attanasi), who is also one of the authors of this paper. About one third of enrolled students per year were involved in the experiments, i.e. 3366 students as a whole.[5] In each of the six consecutive academic years where the classroom experiments were held, the following features were homogeneous: age (almost all students being 19 or 20 years old), gender (45% female), nationality (around 80% Italians), and field of study (all were students in Economics). We kept the number of traders essentially constant (40 subjects) across the 84 experimental sessions we ran.[6] In 42 (i.e., half) of the sessions the DA treatment was implemented (1686 subjects in total), while in the remaining 42 sessions the OTC treatment was implemented (1680 subjects in total).

Common features. Here we describe features of the design common to each of the 84 sessions:

- *Number and length of trading periods*. Each experimental session consists of nine trading periods.[7] The nine periods are partitioned into three phases, with each phase consisting of three periods. The first six periods have equal clock time length, namely 120 s per period, hence the first and the second phase last 360 s each, that is, 6 min per phase. The last three periods (third phase) have a shorter clock time length, namely 60 s each, that is 3 min in total for the third phase.[8]
- *Market structure*. The 40 subjects in each session are divided equally into buyers and sellers (20 buyers and 20 sellers for each session). As in Cason and Friedman (1996), subjects are allowed to trade only one unit per period. During each period only one unit of a homogeneous good can be bought/sold by a specific buyer/seller. In particular, every seller owns only one unit of the good. Each buyer (seller) is assigned a valuation (a cost) for the single unit of the good he/she has to buy (sell). The buyer's valuation sets the maximum amount he/she can spend for one unit of the good, while the seller's cost sets the minimum amount he/she has to receive for his/her unit. As in Smith (1962), valuations and costs are exogenously given. In particular, valuations and costs are distributed so that each buyer (seller) has a different valuation (cost) from those of all other buyers (sellers). By sorting individual valuations from the highest to the lowest, and costs from the lowest to the highest, we obtain a demand and a supply curve, respectively. The competitive-equilibrium price and quantity are determined by the intersection of these two curves (see Fig. 1). In particular, to check that the experimental outcomes are independent of the initial conditions, we implemented three different distributions of valuations/costs, leading to equilibrium quantity-price combinations *A, B* and *C* in Fig. 1.[9]
- *Budget constraints*. Two budget-like constraints are imposed. A feasibility constraint imposes that buyers cannot bid over their own valuation, and sellers cannot ask under their own cost. An intertemporal constraint dictates that wealth cannot be transferred through different periods, hence a buyer cannot use in the next periods the amount not spent in the current period, and a seller cannot sell in the next periods the unit of the good not sold in the current period.
- *Information*. At the beginning of each phase, subjects are informed that the phase is constituted by three periods. In each period, subjects do not know the distributions of valuations and costs in the market.[10] During each phase, each subject is given three pieces of information: his/her role (either buyer or seller), his/her redemption value (either valuation or cost) for the single unit of the good, and his/her ID. These are private information and always appear on the subject's screen. It is common knowledge that while subjects' roles and redemption values are kept constant in the three periods of the phase, their IDs are reshuffled at every period. This prevents subjects from identifying trading counterparts in a given period on the basis of IDs learned in previous periods. At the end of each phase, roles are kept constant while redemption values are reshuffled. Therefore, a subject being a buyer (seller) in the first phase

[4] The English translation of the instructions is provided as an electronic supplementary material of this paper: at www.beta-umr7522.fr/IMG/UserFiles/Attanasi/instr-otc.pdf.

[5] Participation to the classroom experiment was voluntary. Another one third of enrolled students per year participated in a related market (classroom) experiment, whose results are reported in a companion paper (Attanasi et al., 2016).

[6] To be precise, in 81 sessions we had 40 subjects and in 3 sessions we had 42 subjects.

[7] This feature of the design is in line with previous classroom-experimental studies of DA markets (e.g., Smith, 1962) and of OTC markets (Holt, 1996).

[8] As it will be explained more extensively below, the reason for introducing a shorter third phase is twofold: to check whether experimental outcomes are robust to further learning on the part of the subjects, and whether lack of time influences experimental outcomes in a different way in different treatments.

[9] Equilibrium combination *A*, $(q^*, p^*) = (17, 64)$, is obtained from a distribution of valuations v and costs c with $\max v = 98$, $\min c = 32$ and a 2-integer distance between two subsequent valuations or costs, i.e. $v \in \{98, 96, \ldots, 62, 60\}$ and $c \in \{32, 34, \ldots, 68, 70\}$. Similarly, equilibrium combination *B*, $(q^*, p^*) = (14, 70)$, is obtained with $\max v = 98$, $\min c = 44$ and a 2-integer distance between two subsequent valuations or costs; equilibrium combination *C*, $(q^*, p^*) = (14, 58)$, is obtained with $\max v = 86$, $\min c = 44$ and same 2-integer distance.

[10] Indeed, the experimental software only allows players to enter numbers with one or two digits in the bid/ask box. Hence, subjects easily understand that the support of the valuations and costs is constituted by integer numbers between 0 and 99.

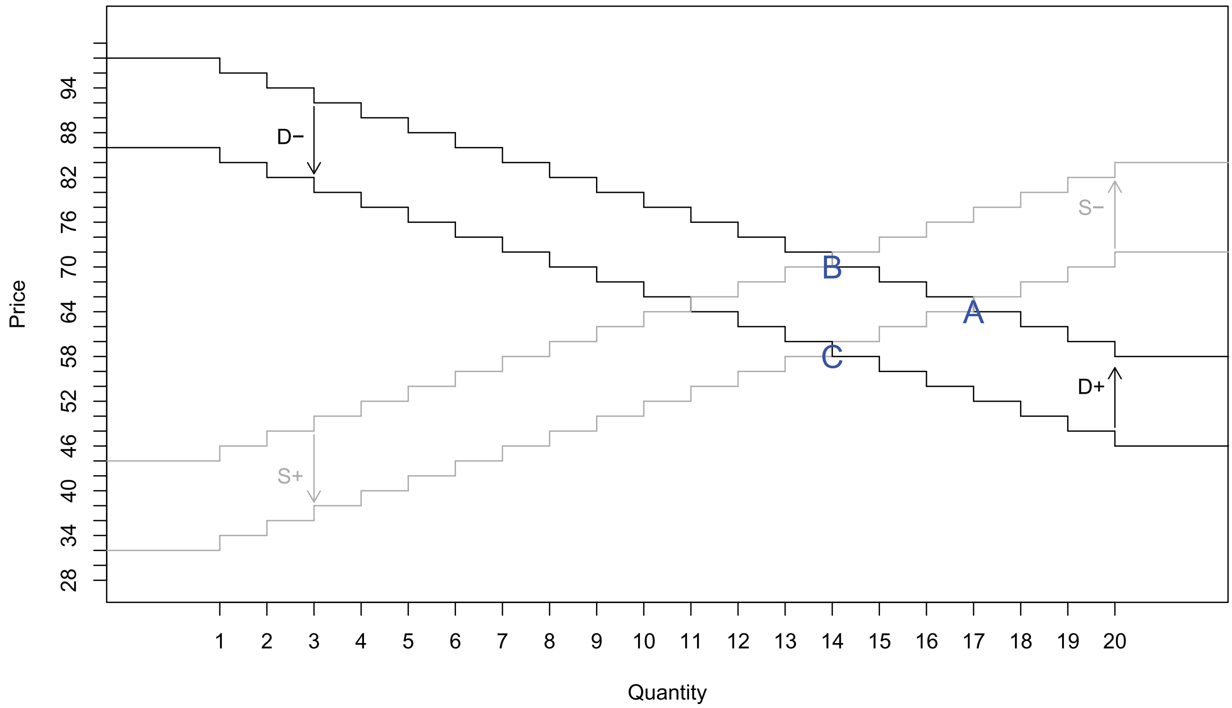

Fig. 1. Competitive-equilibrium quantity and price for different distributions of valuations/costs, and after different shocks.

will be assigned the same role but most likely a different valuation (cost) in the next ones. To prevent repeated-game effects, subjects are informed about the existence of a new phase only at the end of the previous one.

- *Incentives*. At the end of each period, each subject sees on the screen his/her payoff as the difference between valuation and closing price – if he/she is a buyer – or between closing price and cost – if he/she is a seller. If a subject does not trade his/her commodity unit within the period, his/her payoff is equal to zero. As it is common in many classroom experiments, and because the exceptionally large number of students involved in our setting would make paying them too expensive, we do not use monetary incentives. However, we give students a non-monetary incentive to play effectively: at the end of each of the three phases, subjects are ranked according to their corrected total profit in that phase.[11] We then asked the four subjects having earned the highest (lowest) total profit in that phase to stand up so as to be publicly praised (flouted) for their performance by classmates.[12]

Main treatments. The main treatment variable is the *trading mechanism* used to allow buyers and sellers to interact within a trading period. We have two trading mechanisms, DA and OTC, with 42 experimental sessions per treatment. In both treatments, once a subject's quote is accepted by a counterpart, the closing price appears on the screens of all subjects, not only of the two traders. In this way prices of closed transactions are made public in chronological order. However, two main features distinguish the DA from the OTC treatment:

- *Public vs. private quotes*. We define a buyer's (seller's) bid (ask) as "public" if it can be addressed to all sellers (buyers) in the market and it is disclosed to all buyers and sellers (also to those no more in the market). Conversely, we define a quote as "private" if it can be addressed to only one counterpart in the market and only this subject can observe it. In particular:
  - In the DA treatment, buyers and sellers post their bids and asks publicly, so that the bid-ask history of the market is public information. Hence, every buyer (seller) is always informed about the best bid (ask) on the market.
  - In the OTC treatment, each subject looks for the best counterpart through private bids and asks. More precisely, a subject can send only one quote at a time to a single counterpart, by indicating the amount of the quote and the counterpart's ID. He/she may withdraw the quote at any moment during a period (e.g., because the counterpart does not reply soon after receiving it), and make a new quote that differs either in terms of the amount, the counterpart's ID or both.[13]
- *Bid/ask improvement rule*. The bid/ask improvement rule imposes that, in order to make a valid quote, a subject has to improve on the existing situation. A buyer has to submit a bid higher than the current highest bid (ascending auction), and a seller has to submit an ask lower than the current lowest ask (descending auction). When a buyer and a seller reach an agreement, they exit the market, the standing bids and asks are removed, and new bids and asks can be submitted.

[11] Profits are in fact corrected: since redemption values are assigned randomly, subjects who are less lucky would be penalized. Therefore, we implement a correction factor that, for buyers, is proportional to the distance between their valuation and the highest valuation in the market and, for sellers, is proportional to the distance between their cost and the lowest cost in the market. Before the beginning of the experiment, subjects are informed about the way profits will be corrected.

[12] On the methodology of classroom experiments and the issue of whether monetary incentives are really necessary to motivate experimental subjects, see Holt (1999), Guala (2005), and Bardsley et al. (2009). For example, Camerer and Hogarth (1999) review 74 experiments with no, low, or high performance-based monetary incentives, and find that the modal result has no effect on mean performance. More generally, although we acknowledge that monetary incentives are important in market experiments, our study is comparative (behavior in OTC is analyzed in contrast to behavior in DA). Hence, the absence of monetary incentives should not affect our main comparative results.

[13] Notice that it is possible that a subject receives more than one offer at a time (because his/her ID has been indicated by more than one counterpart during the same time interval). In this case, offers are automatically ranked, so that the best possible deal always appears on the top of the subject's screen.

- In the DA treatment, the bid/ask improvement rule holds. Every subject is informed about the highest bid and the lowest ask existing in the market, and a transaction between a buyer and a seller is realized when either the former accepts the standing lowest ask of the sellers' descending auction or the latter accepts the standing highest bid of the buyers' ascending auction. The closing price is the accepted quote.
- In the OTC treatment, the bid/ask improvement rule does not hold: subjects do not observe the best bid and ask present in the market, and, whenever they withdraw a quote, they can replace their previous bid (ask) with a lower (higher) one in the new quote.

Additional treatments. We define an *exogenous shock* as a modification in the buyers' valuations (i.e., a shift in the market demand curve) or a modification in the sellers' costs (i.e., a shift in the market supply curve) that leads to a change in the competitive quantity q^* and the competitive price p^*. Further treatment variables are: the possibility that an exogenous shock is introduced in the second phase; whether this shock concerns the buyers' valuations or the sellers' costs; whether valuations (or costs) are increased or decreased.

- *No shock vs. shock*. In 36 over 84 experimental sessions no shock is applied in the second phase. In all phases of the experiment, the distribution of valuations/costs is always the same, leading to either A, or B or C in Fig. 1 (6 experimental sessions per treatment for each quantity-price combination).[14] In the remaining 48 experimental sessions a shock is applied to either demand or supply for both the DA treatment (24 sessions) and the OTC treatment (24 sessions). In all these sessions, a shock occurs at the beginning of the second phase (period 4), and is maintained during the whole second phase (periods 4–6) and during the third phase (periods 7–9). The third phase is mainly run in order to check whether further learning on the part of the subjects may have different effects on the experimental outcomes when a specific shock is applied.
- *Types of shocks*. We implement four different types of shocks (6 experimental sessions for each type of shock, per treatment). Each type of shock is characterized by two features: whether the variation concerns the support of the valuations or the support of the costs; whether all redemption values in a support are increased or decreased by the same amount.[15] Shocks produce shifts in either the demand or the supply curve and thus lead to a change in the predicted competitive quantity q^* and competitive price p^*. By defining as *negative* (*positive*) a shock that leads to an decrease (increase) of the competitive quantity q^*, the four shocks can be classified as:[16]
  1. a negative (downward) shift of demand, indicated as D^- and leading to a decrease of both q^* and p^* (in Fig. 1, from A to C);
  2. a positive (upward) shift of demand, indicated as D^+ and leading to an increase of both q^* and p^* (in Fig. 1, from C to A);
  3. a negative (upward) shift of supply, symbolized by S^- and determining a decrease of q^* and an increase of p^* (in Fig. 1, from A to B);
  4. a positive (downward) shift of supply, symbolized by S^+ and determining an increase of q^* and a decrease of p^* (in Fig. 1, from B to A).
- *Information*. Subjects are given no information about the fact that a shock has been applied in the second phase and maintained in the third phase, nor about the type of shock.

Table 1
Number of sessions per treatment.

	No Shock	D^-	D^+	S^-	S^+
DA	18	6	6	6	6
OTC	18	6	6	6	6

Table 1 summarizes our experimental treatments by indicating the absolute number of sessions that we ran for each market mechanism (main treatments: DA and OTC), without shock and for each of the four types of shock (D^-, D^+, S^-, S^+). As Table 1 shows, we ended up having 10 treatments, each one characterized by a different mechanism-shock combination.

3. Behavioral predictions

We base our behavioral predictions on a very simple model of search under incomplete information. This model is a simplified version of those presented in Duffie et al. (2005), Duffie et al. (2007), and Duffie (2012).

The market is populated by two types of agents: buyers (b) and sellers (s). Each agent is exogenously assigned to be either a buyer or a seller with probability 0.5. Each buyer and seller could be either of the *intra-marginal type*, that is, her valuation is higher, respectively, her cost is lower than the equilibrium price; or of the *extra-marginal type*, that is, her valuation is lower, respectively, her cost is higher than the equilibrium price. We denote as μ_{bi} and μ_{si}, respectively, the fractions of intra-marginal buyers and sellers; and as μ_{be} and μ_{se} the fractions of extra-marginal buyers and sellers. We have that:

$$\mu_{bi} + \mu_{be} + \mu_{si} + \mu_{se} = 1.$$

At the beginning of the trading period, each agent is assigned exogenously to one of these four types. Sellers are endowed with only 1 unit of the good. Whenever a trade occurs, the buyer and the seller exit the market. When bargaining with a specific counterpart, agents cannot search for alternative trading partners. Trading periods are independent of each other.

Agents are risk neutral and they are randomly matched with constant intensity λ. This intensity may be considered as the sum of the intensity of agent a contacting other agents and the intensity of the same agent a to be contacted by other agents being on the other side of the market. Denote as p the trading price, as v_b the exogenous valuation of a buyer, and as c_s the exogenous cost of a seller. In particular, with v_{bi} (resp., v_{be}) we refer to the valuation of an intra-marginal (resp., extra-marginal) buyer, and with c_{si} (resp., c_{se}) to the cost of an intra-marginal (resp., extra-marginal) seller. Similarly, we denote as p^* the competitive equilibrium price, which is also exogenously given. The equilibrium quantity, q^*, is given by the number of intra-marginal sellers at the beginning of the trading period. We assume $min(v_{be}) > min(c_{si})$, and $max(c_{se}) < max(v_{bi})$, so that trade may occur between extra-marginal and intra-marginal players. However, trade never occurs between an extra-marginal buyer and an extra-marginal seller. The probability of a trade occurring is given by

$$\lambda(\mu_{bi}\mu_{si} + \mu_{be}\mu_{si} + \mu_{bi}\mu_{se}).$$

[14] In particular, we have 12 no-shock sessions with A as predicted equilibrium combination in all trading periods (6 under DA and 6 under OTC); 12 no-shock sessions with B (6 under DA and 6 under OTC); 12 no-shock sessions with C (6 under DA and 6 under OTC).

[15] This amount is 12 integers for each shock; i.e., it is the distance between the two demand functions in Fig. 1, that is equal to the distance between the two supply functions in the same figure.

[16] Given that two of the four types of shock have A as pre-shock predicted combination, of the 24 sessions with shocks for each main treatment (DA and OTC), 12 have predicted combination A, 6 have predicted combination B, and 6 have predicted combination C before the shock.

As in Duffie (2012), the trading price is determined as the weighted sum of the valuation of the buyer and the cost of the seller. That is:

$$p = (1-q)v_b + qc_s,$$

where $q \in [0, 1]$ is defined as the *bargaining power* of the buyer.[17] We take q as follows:

$$q = \frac{\rho(1+\lambda\mu_{si})}{\rho(1+\lambda\mu_{si}) + (1-\rho)(1+\lambda\mu_{bi})},$$

with $\rho \in [0, 1]$. This implies that the bargaining power of the buyer depends positively (negatively) on the fraction of intra-marginal sellers (buyers) still on the market: when competition on the sellers' side (proxied by μ_{si}) increases, the bargaining power of the buyer increases; vice versa, when competition on the buyers' side (proxied by μ_{bi}) increases, this bargaining power decreases. Traders' matching intensity λ amplifies this effect (q depends positively on λ if $\mu_{si} > \mu_{bi}$).

The equilibrium of this market is reached when there are no more trades possible, so that $\mu_{si} = \mu_{bi} = 0$. Thus, $q = \rho$, a constant, with

$$\mathbb{E}(p) = (1-\rho)\mathbb{E}(v_b) + \rho\mathbb{E}(c_s) = p^*.$$

Furthermore, when the intensity $\lambda \to \infty$,

$$q = \frac{\rho\mu_{si}}{\rho\mu_{si} + (1-\rho)\mu_{bi}}.$$

In our experiments, $\rho = 0.5$, as the market is symmetric. This implies that, in equilibrium, buyers and sellers have the same bargaining power.

Notice, however, that there still may be two sources of potential inefficiency. The matching intensity λ generates a market friction that disappears as λ tends to infinity. The other source is given by the way in which agents are matched. If all trades occur between infra-marginal players, then the symmetry of the market is maintained within a trading period and inefficiencies are not possible. Nevertheless, with some probability, a matching can occur between an extra-marginal and an infra-marginal players. These matches modify the market symmetry and generate inefficiencies. While the OTC market may be affected by both sources of inefficiency, the DA market is only affected by the latter. This is because information is public in the DA setting, and therefore $\lambda \to \infty$, whilst in the OTC market $\lambda < \infty$.

Based on this very simple model, we make the following behavioral predictions:

(i) The average trading price of the OTC market may deviate from the equilibrium price more than in the DA market, because of the additional friction given by λ. This would also affect the quantity traded on the market.
(ii) The number of extra-marginal players that are able to trade is higher in the OTC setting. This generates a deviation from the competitive market surplus.
(iii) Market adjustments happen more rapidly as λ increases: an exogenous shock on the equilibrium price p^* would be absorbed more rapidly in DA than in OTC.

4. Results

The basic measure on which we rely to compare the performance of DA and OTC mechanisms is the *efficiency index* defined by Smith (1962) and used, among others, by Gode and Sunder (1993).

Table 2
Efficiency index in the no-shock treatment.

	DA		OTC	
Period 1	87.8		68.3	
Period 2	94.7		84.8	
Period 3	93.3		84.6	
Phase 1		91.9		79.2
Period 4	95.2		92.1	
Period 5	94.2		92.7	
Period 6	93.9		89.6	
Phase 2		94.4		91.5
Period 7	93.9		91.6	
Period 8	93.0		83.6	
Period 9	92.4		80.1	
Phase 3		93.1		85.1
Total		93.1		85.3

It is the ratio between the total uniperiodal profit actually earned by all traders in a market (i.e., the sum of consumer and producer realized market surplus), and the maximum total uniperiodal profit that could have been earned by all traders in the market (i.e., the sum of consumer and producer equilibrium surplus). The efficiency index goes from 0 (minimal efficiency) to 100 (full efficiency) percentage points, with full efficiency being reached if all subjects trade at the equilibrium price.

The efficiency index, however, says nothing about the causes of the inefficiency. To better understand these causes, we also compare the *quantity actually traded* in these markets with the predicted competitive quantity, and study the *pattern of closing prices* under the DA and OTC mechanisms. Moreover, following Rust et al. (1993), we decompose inefficiency into two main components: *intra-marginal inefficiency* and *extra-marginal inefficiency*. There is intra-marginal inefficiency (henceforth *IM-inefficiency*) when two intra-marginal traders – i.e., a buyer with a valuation higher than the competitive price and a seller with a cost lower than the competitive price – do not exchange. Extra-marginal inefficiency (*EM-inefficiency*), by contrast, occurs when an extra-marginal trader – i.e., a buyer with a valuation lower than the competitive price or a seller whose cost is higher than the competitive price – exchanges with an intra-marginal trader.

First we compare the relative performance of DA and OTC mechanisms in the 36 sessions (18 per mechanism) without shocks. Then we perform the same analysis for the 48 sessions (24 per mechanism) characterized by an exogenous shock in period 4, that is, at the beginning of the second phase. In order to facilitate comparison between the treatments without shocks (Section 4.1) and those with shocks (Section 4.2), we report results for the entire experimental session (periods 1–9) and for the first phase (periods 1–3), the second phase (periods 4–6), and the third phase (periods 7–9) separately.[18]

4.1. DA and OTC without shocks

Table 2 reports the *efficiency index* for the DA and OTC markets respectively. Recall that the informational advantage of the DA over the OTC mechanism is due to the fact that in the former the entire history of bids and asks is public information, while in the latter only the closing prices are made public. As expected, this makes the DA market more efficient, on average, than the OTC market. More precisely, over periods 1–9 we observe an average efficiency index of 93.1 in the DA market: this result is in line with past findings of Gode and Sunder (1993), and Cason and Friedman (1996).

[17] This weighted sum can be thought as a Rubinstein's bargaining game in which either the buyer or the seller are asked to submit a post with probability q and $1-q$, respectively.

[18] All data are available upon request.

We also find that the average efficiency index is greater in the DA than in the OTC market (85.3), with this difference being significant at 1% level (see results of Mann-Whitney test in the first row, first column of Table A.1 in the Appendix, rejecting the null hypothesis of equal population medians with *P-value* = 0.000). This significant loss of efficiency in the OTC market is quantified in 7.8 efficiency points on average across all trading periods.

As it has been already shown in other experimental studies (see Cason and Friedman, 1996, and references therein), experience in market experiments, i.e. learning, increases the efficiency of a market institution. In our study this is true, in particular, for the OTC mechanism. Over the first phase of the experiment (periods 1–3) its average efficiency index is in fact 79.2, which is more than 10 points smaller than the average efficiency index of the DA mechanism (91.9) and more than 20 points far from full efficiency. This situation leaves more room for efficiency gains due to traders' learning. In fact, in passing from the first to the second phase of the experiment (periods 4–6), the average efficiency of the OTC mechanism increases by more than 12 efficiency points (from 79.2 to 91.5) and the gap with the average efficiency of the DA mechanism (94.4) reduces to just 2.9 efficiency points. However, the improvement in the efficiency of the OTC mechanism disappears when the trading time shortens. In the third phase of the experiment (periods 7–9), when the trading time in each period is only 60 s, that is half the time of all previous periods, the efficiency index of the OTC mechanism significantly decreases, and passes from 91.5 (second phase) to 85.1 (third phase). This loss of efficiency appears to be due to the lack of time to privately look for the best counterpart in the OTC market. This supposition is confirmed by the fact that in the DA market, which is less affected by lack of time thanks to the faster public double-auction trading procedure, the average efficiency in the third phase (93.1) is only slightly smaller than the average efficiency in the second phase (94.4). It is important to notice, however, that the average efficiency index for the OTC market in the third phase of the experiment (85.1) is significantly greater (6 efficiency points) than in the first phase (79.2). Therefore, it seems that in the OTC market learning effects partially compensate the increased difficulty in finding the best counterpart when the time available is halved.

The above findings are summarized as follows:

Result 1 (Efficiency). The DA market is significantly more efficient than the OTC market. The efficiency gap can be quantified in 7.8 efficiency points over all trading periods. Learning partially offsets this efficiency gap, although this effect is smaller the smaller the length of the trading period.

Now we focus on the analysis of the causes of the higher inefficiency of the OTC mechanism. This may come from two sources: the actual traded quantity q being different from the competitive quantity q^*; and/or closing prices converging to a price that is different from the competitive price p^*.

Table 3 reports, for each of the nine trading periods, the fraction of sessions where the *traded quantity* is different than the competitive one. Indeed, if $q < q^*$, then profitable trades between some intra-marginal buyer and some intra-marginal seller have not taken place. If $q > q^*$, then some commodity units that should have been left out of the market have instead been exchanged: either some extra-marginal buyer managed to buy from an intra-marginal seller, or some extra-marginal seller managed to sell his/her unit to an intra-marginal buyer, or both. Notice that exchange between two extra-marginal traders is impossible: extra-marginal buyers have valuations below the competitive price, while extra-marginal sellers have costs above the competitive price. Therefore, the set of possible agreements between these two categories of traders is empty.

Table 3
Traded quantity q vs. competitive-equilibrium quantity q^* in the no-shock treatment (for each mechanism, in percentage over all sessions within the same period).

	DA			OTC		
	$q < q^*$	$q = q^*$	$q > q^*$	$q < q^*$	$q = q^*$	$q > q^*$
Period 1	33.3	33.3	33.4	100.0	0.0	0.0
Period 2	0.0	38.9	61.1	55.6	33.3	11.1
Period 3	11.1	38.9	50.0	44.4	27.8	27.8
Phase 1	14.8	37.0	48.1	66.7	20.4	13.0
Period 4	5.6	22.2	72.2	33.3	27.8	38.9
Period 5	11.1	27.8	61.1	22.2	38.9	38.9
Period 6	11.1	27.8	61.1	50.0	22.2	27.8
Phase 2	9.3	25.9	64.8	35.2	29.6	35.2
Period 7	11.1	22.2	66.7	44.4	27.8	27.8
Period 8	11.1	50.0	38.9	72.2	11.1	16.7
Period 9	27.8	27.8	44.4	72.2	22.2	5.6
Phase 3	16.7	33.3	50.0	63.0	20.4	16.7
Total	13.6	32.1	54.3	54.9	23.5	21.6

Table 3 shows that in the DA market, $q < q^*$ in only 13.6% of all trading periods. This result is consistent with existing experimental evidence about DA (see, e.g., Gode and Sunder, 1993, Cason and Friedman, 1996), and appears to be due to the informational features of the DA mechanism. Since in these markets the current highest bid and the current lowest ask are public information, it is easy for intra-marginal buyers (who have higher valuations than extra-marginal buyers) and intra-marginal sellers (who have lower costs than extra-marginal sellers) to propose deals that can be accepted by an intra-marginal counterpart. This aspect of the DA mechanism is not significantly affected by learning or the duration of the trading period, as the percentage of periods for which $q < q^*$ remains quite stable over the three phases of the experiment.

In the OTC market, $q < q^*$ much more frequently than in DA market, namely in 54.9% of all trading periods. Our explanation for this result is that, since in OTC markets negotiations are conducted on a one-to-one basis, intra-marginal traders can easily miss the possibility of closing a profitable transaction before the end of the trading period, due the limited trading time. To support this explanation, notice that, when traders become more experienced, the percentage of periods for which $q < q^*$ strongly decreases: it is 66.7% on average in the first phase, and only 35.2% on average in the second phase. This corresponds to a notable increase in the efficiency of the OTC mechanism (+12.3 efficiency points), as reported in Table 2 above. Correspondingly, the decrease in efficiency from the second to the third phase in the OTC market (−6.4 efficiency points) is associated with a significant increase (from 35.2% to 63% on average) in the percentage of periods for which $q < q^*$. In the OTC mechanism, therefore, the positive effects of learning on the quantity traded disappear as the length of the trading period decreases.

These findings can be summarized as follows:

Result 2 (Traded quantity). The DA trading mechanism only rarely delivers a traded quantity q lower than the competitive quantity q^*. This is independent of traders' learning. Conversely, the OTC trading mechanism very often delivers $q < q^*$; learning about the trading mechanism significantly reduces the number of trading periods where $q < q^*$, although this effect is smaller the smaller the length of the trading period.

The result that in the OTC market $q < q^*$ can be related to the *pattern of closing prices*. If the market converges to an average closing price below (above) the competitive price p^*, intra-marginal sellers (intra-marginal buyers) – who in a competitive market would have sold (bought) a unit of the good – are left

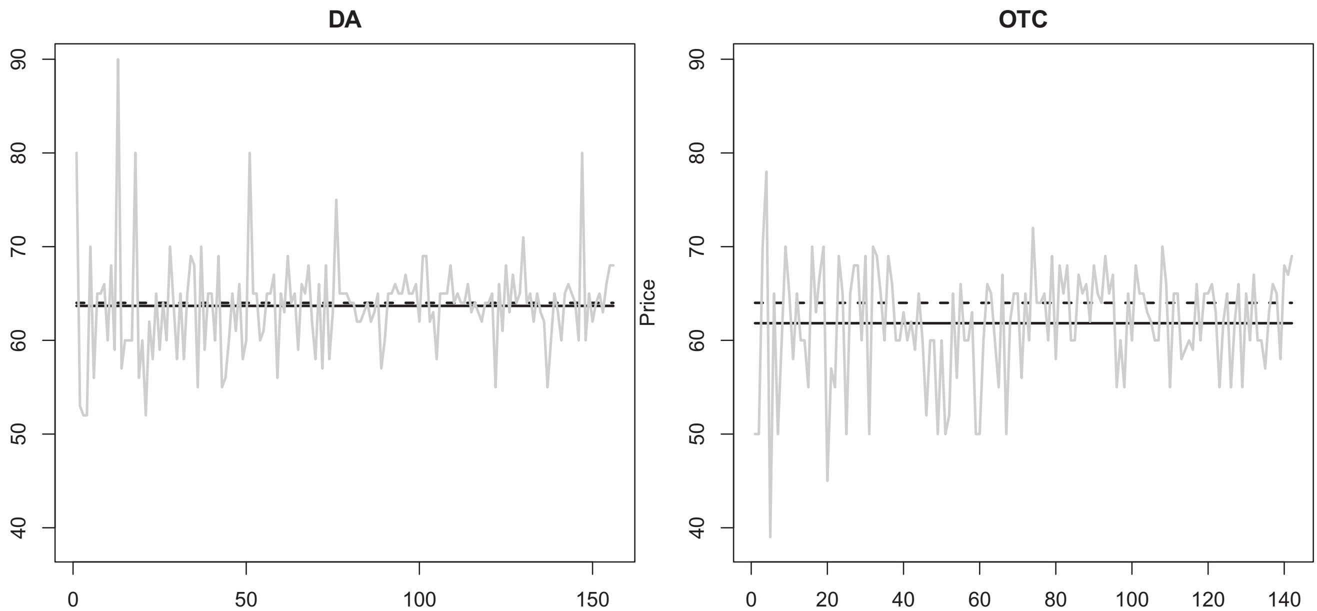

Fig. 2. Closing price patterns in a DA market (left panel) and an OTC market (right panel) in a no-shock treatment. Dashed line: competitive price; continuous line: average closing price.

out of the market. This, in turn, reduces the quantity exchanged and generates inefficiencies. We therefore take a closer look at the pattern of closing prices and at their possible convergence to the competitive equilibrium.

In the left panel of Fig. 2, we draw the pattern of closing prices in all trading periods of a single DA experimental session, while in the right panel we do the same for a single OTC session (as we will see in a moment, what happens in these two specific sessions is representative of what occurs in all other sessions). For each of the 9 periods of both sessions, the predicted equilibrium combination is A in Fig. 1, i.e. $(q^*, p^*) = (17, 64)$. In both panels of Fig. 2, the units traded are plotted in abscissas according to the chronological order in which they have been traded in each period (the first unit traded in period 1 comes first on the abscissas line, the second unit traded in period 1 comes second, etc.), with units traded in period 2 plotted after those traded in period 1, and so on until period 9. The prices corresponding to each traded unit are plotted in ordinates; the dashed line corresponds to the predicted competitive price, while the continuous line expresses the average closing price over all 9 periods.

Fig. 2 shows that price convergence to the average closing price occurs in both markets. However, in the DA treatment the average closing price almost coincides with the competitive price (the continuous and dashed lines are superposed). In contrast, in the OTC treatment the average closing price is clearly below the competitive price. The latter result might be explained by the fact that, despite the experimentally-imposed symmetry between the role of buyer and the role of seller, sellers feel much more pressure than buyers in finding a trading counterpart. They want to get rid of the unit of the good they own, and thus are willing to sell it cheaply (see Feldhütter, 2012).

As a matter of fact, the average share of the total surplus allocated to buyers in the DA market is 54.8%; while it is equal to 60% in the OTC. This difference is significant at 1% level using a Wilcoxon rank sum test.

This pattern of closing prices does not characterize only the specific DA and OTC experimental sessions represented in Fig. 2, but holds for all the DA and OTC experimental sessions without shocks. This is shown in Fig. 3, where we report the histogram of the relative deviations from the competitive price for periods 4–6 of all experimental sessions with no shock. Recall that (see Table 2), among the three phases of the experiment, the highest efficiency is found in the second phase (periods 4–6) and that this holds for both trading mechanisms. Given that the maximum (full) efficiency is found by construction when $(p, q) = (p^*, q^*)$, we guess that if convergence to the competitive equilibrium were reached, this would happen in the second phase. Therefore, we plot the histogram of $\Delta p_i^* = (p_i - p^*)/p^*$, where p_i is the closing price of commodity unit i in periods 4–6 and p^* is the competitive price.[19] In the left panel of Fig. 3, we report the histogram of Δp_i^* for the DA treatment. Although this distribution is slightly skewed on the left, it is roughly centered around 0. This confirms that, over *all* DA sessions with no shock, the closing prices converge to p^* in the second phase of the experiment. In contrast, the histogram for the OTC market – Fig. 3, right panel – shows that relative deviations of closing prices are almost normally distributed and that their mean is slightly below 0. This confirms that, even when we consider *all* OTC experimental sessions, the closing prices converge to a price below the competitive price. This, in turn, implies that some intra-marginal sellers are left out of the market, that the exchanged quantity remains lower than the competitive quantity, and that inefficiencies emerge.

The findings summarized in Figs. 2 and 3 are also confirmed by the dynamic panel data regression of closing prices in Table A.2 in the Appendix. In both main treatments DA and OTC, autocorrelation coefficients of lag prices are all positive and lower than 1, which confirms price convergence under both trading mechanisms. Furthermore, in the joint regression, the OTC-treatment dummy is significant and negative, thereby confirming that closing prices are on average lower in the OTC than in the DA treatment.[20]

Therefore, the following result can be stated:

[19] Notice that, for each trading mechanism (DA and OTC), we do not find significant differences in experimental outcomes across the three different distributions of valuations/costs (i.e., among A, B and C in Fig. 1, for the 18 sessions without shocks in each main treatment). Therefore, without loss of generality, given a trading mechanism, we can analyze Δp_i^* by pooling data of all sessions with no shock.

[20] Since we have a large panel of price processes for each period, we use the System GMM estimator developed by Blundell and Bond (1998). We run a regression for each treatment separately and then a joint regression with both treatments.

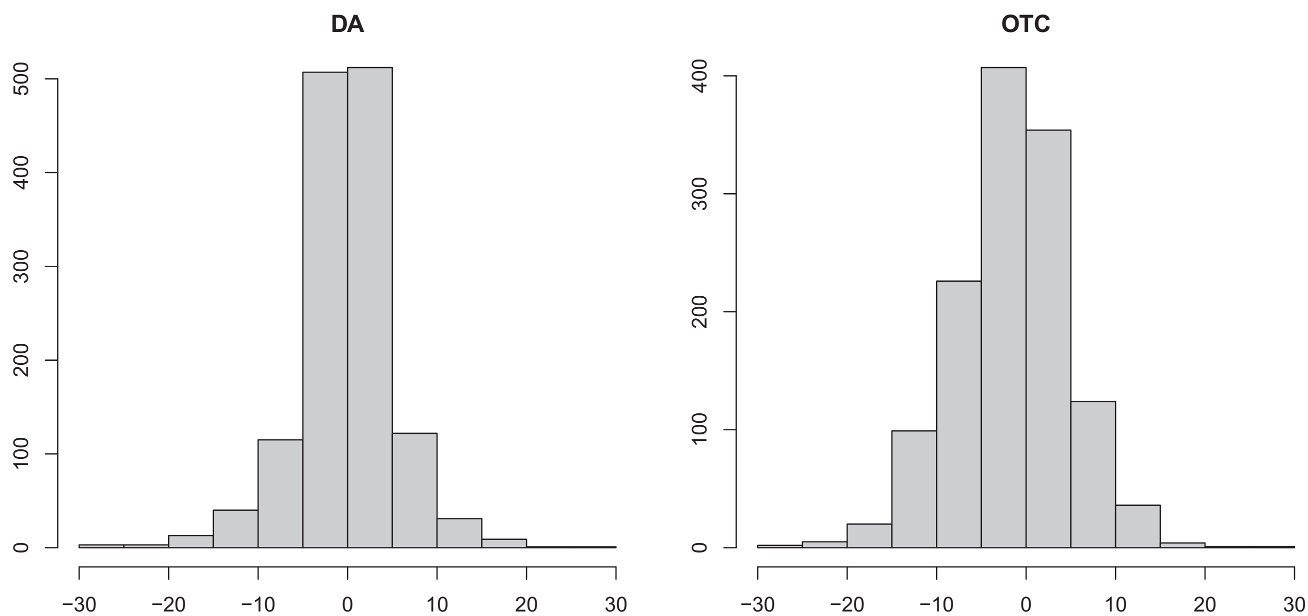

Fig. 3. Histograms of the relative deviations of closing prices from the equilibrium price, periods 4–6 in DA (left panel) and OTC (right panel), in no-shock treatment.

Result 3 (Closing price). In the DA treatment the average closing price almost coincides with the competitive price, while in the OTC treatment the average closing price is significantly lower than the competitive price. All this also holds in the second phase of the experiment, where closing prices are more likely to converge to the equilibrium price.

Result 3 is further explored in a regression analysis of efficiency that is based not only on the data for periods 4–6, but on data of all periods (see Table A.3 in the Appendix).[21] This regression shows that efficiency in DA markets is increasing as the average trading price $\bar{p}$ approaches the equilibrium price, p^*, that is, as the absolute difference $|\bar{p} - p^*|$ shrinks. By contrast, in the OTC market a decrease in $|\bar{p} - p^*|$ does not lead to any statistically significant change in efficiency. This finding is consistent with our descriptive analysis about the two markets. The DA market exhibits a very consistent behavior, in that $\bar{p}$ is often close to p^* (for about 40% of our trading periods, the absolute difference is lower than 1 unit). Therefore, even a very slight change in the average trading price can entail a change in the efficiency for this market. Conversely, in the OTC mechanism this difference between $\bar{p}$ and p^* is often large (for more than 76% of the trading periods $\bar{p}$ is more than 1 unit away from p^* and, in 74% of them, this difference is negative). Therefore, there is not sufficient variation for the absolute difference to have a significant impact on efficiency.

Notice that this is also consistent with the informational features of the two markets. In the DA market, the bid-ask improvement rule drives out extra-marginal players from the game as they can hardly beat the quotes made by intra-marginal players. The pricing feature of the market becomes very important in this context, as slight deviations from the equilibrium price (and for a given equilibrium quantity), can change the total surplus by excluding extra-marginal players or including intra-marginal ones. In the OTC market, there is no information about the bids and asks of other players. Therefore, the mass of trades becomes a more crucial determinant of market efficiency. A traded quantity closer to the equilibrium quantity generates by itself more market efficiency in the OTC mechanism. Although this may also cause the average trading price to be closer to the equilibrium price, the latter effect seems to go through only via the distance between the traded and the equilibrium quantity.[22]

The analysis can be brought further. To better understand the efficiency gap between the DA mechanism and the OTC mechanism, it is useful to decompose the loss of surplus generated by these two market mechanisms into *IM-inefficiency*, which emerges when two intra-marginal traders do not exchange; and *EM-inefficiency*, which occurs when an extra-marginal trader exchanges with an intra-marginal trader.

There is a somewhat tricky relationship between IM-inefficiency, EM-inefficiency, the traded quantity q, and the competitive quantity q^*. First, IM-inefficiency is linked to a decrease in the traded quantity: if two intra-marginal traders do no exchange, then q cannot be greater than q^*. EM-inefficiency, in contrast, could be linked to an increase in the traded quantity, though it can be present also if q is unchanged. To see why, recall that exchange between two extra-marginal traders is impossible. Thus, an extra-marginal trader always trades a commodity unit with an intra-marginal trader, and in so doing he/she displaces some intra-marginal trader. Two things may happen to a displaced intra-marginal trader: he/she may find another extra-marginal trader with whom he/she trades a commodity unit and in this case q increases; otherwise, he/she may be unable to trade a commodity unit, in which case the quantity q traded on the market does not change. To complicate the picture, when $q < q^*$, both IM-inefficiency and EM-inefficiency can be present. For instance, imagine that intra-marginal buyer $b1$ and intra-marginal seller $s1$ are unable to trade: this decreases the traded quantity and generates IM-inefficiency. However, at the same time, intra-marginal buyer $b2$ trades with extra-marginal seller $s3$ who bumps intra-marginal seller $s2$. This creates EM-inefficiency but

[21] We use a zero-or-one inflated beta regression model, since the dependent variables are bounded in the interval [0, 1] and can take values at the boundaries with positive probability. For a general approach and an extensive description of beta regressions see Ospina and Ferrari (2012).

[22] This is also confirmed by the fact that the same regression analysis conducted by omitting the difference in quantity gives a negative and significant coefficient for the difference between $\bar{p}$ and p^* in the OTC market.

Table 4
Sources of inefficiency (in percentage over total inefficiency) in the no-shock treatment.

	IM-inefficiency		EM-inefficiency	
	DA	OTC	DA	OTC
Period 1	16.6	70.9	83.4	29.1
Period 2	0.0	29.3	100.0	70.7
Period 3	5.5	23.3	94.5	76.7
Period 4	0.0	15.4	100.0	84.6
Period 5	3.1	11.0	96.9	89.0
Period 6	6.1	20.1	93.9	79.9
Period 7	6.6	18.6	93.4	81.4
Period 8	6.8	33.2	93.2	66.8
Period 9	11.8	42.7	88.2	57.3
Total	6.3	26.2	93.7	73.8

does not modify the traded quantity, which remains one unit below q^*.

We can summarize the relationships between IM-inefficiency, EM-inefficiency, q and q^* as follows:

- if $q > q^*$, the only source of inefficiency is EM-inefficiency;
- if $q = q^*$ and realized surplus equals equilibrium surplus, the inefficiency equals 0: all intra-marginal traders have traded their unit and all extra-marginal traders did not trade;
- if $q = q^*$ but realized surplus is lower than equilibrium surplus, then the existing efficiency is certainly due to EM-inefficiency. IM-inefficiency is ruled out because q is not smaller than q^*;
- if $q < q^*$, we certainly have IM-inefficiency, but we may also have EM-inefficiency.

Based on our data – that include the redemption values of all traders, the competitive quantity and price, the equilibrium surplus, the quantity actually traded, and the closing prices of all traded units – we can decompose the loss of surplus associated with a specific trading mechanism (DA or OTC) into its IM-inefficiency and EM-inefficiency components.[23] Table 4 reports the results of our market inefficiency audit, by indicating – separately for the DA mechanism and for the OTC mechanism – the percentage of IM-inefficiency and of EM-inefficiency behind the loss of surplus generated by a specific trading mechanism (notice that, for each mechanism, the sum of the two percentages is 1).

We find that in the DA market IM-inefficiency accounts on average for only 6.3% of total inefficiency, while EM-inefficiency accounts for the residual 93.7%. This is congruous with the data displayed in Table 3, which show that in DA markets the traded quantity q is lower than the competitive quantity q^* only in 13.6% of all market periods (recall that we have IM-inefficiency, possibly associated with EM-inefficiency, only when $q < q^*$). In the OTC setting, by contrast, we have a mixture of IM-inefficiency and EM-inefficiency. However, as in the DA setting, EM-inefficiency plays a more important role: on average across all sessions, IM-inefficiency accounts for only 26.2% of the total market inefficiency. Again, this finding is consistent with the data of Table 3 according to which in the OTC setting q is lower than q^* in 54.9% of all market periods. Furthermore, notice that in the OTC setting, the weight of IM-inefficiency is significantly greater than 50% only in trading period 1, where several inexperienced intra-marginal traders are unable to find the best counterpart within the allowed 3 min. The highest IM-inefficiency is found in period 1 also in the DA setting, although here it only accounts for 16.6% of the loss of surplus. Again, in the DA mechanism public asks/bids facilitate immediate learning of the trading mechanism and reduce the time needed to find the best counterpart to trade with. The findings summarized in Tables 3 and 4 are confirmed by Beta regression analysis of efficiency and IM-inefficiency by treatment (see Table A.3 in the Appendix): in both the DA and the OTC market, an increase in the traded quantity q with respect to the equilibrium quantity q^* increases efficiency and decreases (increases) IM-inefficiency (EM-inefficiency). All these effects are significant at 1% level.

These findings are summarized in the following:

Result 4 (Sources of inefficiency). The source of inefficiency in the DA market is almost exclusively extra-marginal. An important amount of intra-marginal inefficiency is instead detected in the OTC market, though significantly smaller than the amount of extra-marginal inefficiency.

4.2. DA and OTC with shocks

In order to grasp better the functioning of the OTC mechanism and compare it with the functioning of the DA mechanism, we introduce shocks into the picture and study how the efficiency of each mechanism is affected by shocks. Recall that, in our design, shocks are shifts in either the demand or the supply curve that lead to a change in both the competitive quantity q^* and the competitive price p^*. In all 48 experimental sessions with shocks, the shock occurs in period 4 (first period of the second phase) and is maintained until the end of the experiment, i.e. both during the second phase (periods 4–6) and during the third phase (periods 7–9). We implement four types of shock: D^-, which decreases q^* and p^*; D^+, which increases q^* and p^*; S^-, which decreases q^* and increases p^*; and S^+, which increases q^* and decreases p^*.

Table 5 reports the efficiency index for DA and OTC markets in period 4, over periods 4–6 (second phase), and over periods 7–9 (third phase) in the case without shocks (first column) and for each of the four types of shock.[24]

Consider first the DA market. Without shocks, the efficiency index in period 4 is equal to 95.2. When shocks decreasing q^* are implemented (i.e. D^- and S^-), the efficiency index in period 4 is slightly lower: −5 efficiency points for D^- and −3.9 efficiency points for S^-. In contrast, for shocks increasing q^* (i.e. D^+ and S^+), the efficiency index is slightly higher in period 4: +1.6 efficiency points for D^+ and +2.1 for S^+. Over periods 4–6, the efficiency loss associated with negative shocks tends to vanish: for the D^- shock the efficiency index (93.1) approaches the one without shocks (94.4). The same happens for the S^- shock, where the efficiency index (93.6) is even closer to the treatment without shocks. Conversely, the efficiency gap between the baseline treatments and those with positive shocks hangs over (+1.8 for D^+ and +3.2 for S^+). Table 5 shows similar qualitative results over periods 7–9, coupled with a slight decrease of efficiency – independent of the presence of a shock and of the type of shock – due to trading periods of reduced time length. Notice that, given the sign of the shock, no significant asymmetry is detected between shocks concerning the demand function and shocks concerning the supply function in any of periods 4–9.

The main finding is in accord with those presented in other studies of DA markets with shocks (see, e.g., Davis et al., 1993): the temporary efficiency loss provoked in DA markets by shocks D^- and S^- may be explained by the fact that both shocks increase the fraction of extra-marginal traders in the market (D^- increases

[23] It is worth mentioning that, despite the fact that we are discussing and presenting the aggregate effects of intra-marginal and extra-marginal inefficiency, we perform our analysis recording the instances of each type of inefficiency for each trading period.

[24] Although efficiency in periods 1–3 is an important benchmark to compare efficiency *within* a given treatment, we focus here only on efficiency comparison *between* treatments.

Table 5
Efficiency index by main treatment and type of shock.

	No shock			D^-			D^+			S^-			S^+		
	Periods			Periods			Periods			Periods			Periods		
	4	4–6	7–9	4	4–6	7–9	4	4–6	7–9	4	4–6	7–9	4	4–6	7–9
DA	95.2	94.4	93.1	90.2	93.1	91.7	96.8	96.2	93.9	91.3	93.6	94.8	97.3	97.6	96.0
OTC	92.1	91.5	85.1	90.0	88.4	86.4	95.7	93.4	86.0	90.0	89.5	86.7	97.3	94.8	89.7

Table 6
Traded quantity q vs. competitive quantity q^* in the OTC treatment with shocks (in percentage over all periods.

	Period 4			Periods 4–6			Periods 7–9		
	$q < q^*$	$q = q^*$	$q > q^*$	$q < q^*$	$q = q^*$	$q > q^*$	$q < q^*$	$q = q^*$	$q > q^*$
No Shock	33.3	27.8	38.9	35.2	29.6	35.2	63.0	20.4	16.7
D^-	33.3	16.7	50.0	33.3	33.3	33.3	66.7	22.2	11.1
D^+	16.7	50.0	33.3	38.9	44.4	16.7	77.8	5.6	16.7
S^-	33.3	50.0	16.7	33.3	44.4	22.2	44.4	27.8	27.8
S^+	16.7	16.7	66.7	11.1	33.3	55.6	61.1	22.2	16.7

the fraction of extra-marginal sellers while S^- increases the fraction of extra-marginal buyers). This, in turn, increases the probability that extra-marginal traders manage to exchange with some intra-marginal trader and therefore raises the EM-inefficiency of the DA mechanism. However, due to the trading-enhancing features (e.g., public asks/bids) of the DA mechanism, negative shocks are absorbed within few periods.

Compared to the DA market, in the OTC market we observe in period 4 a similarly small efficiency loss due to negative shocks (with respect to 92.1 in the baseline, −2.1 both for D^- and S^-) and a stronger efficiency gain due to positive shocks (+3.6 for D^+ and +5.2 for S^+). Under S^+, in period 4 the efficiency of the OTC mechanism (97.3) reaches exactly the same level as in the DA mechanisms. Thus, we can observe that soon after a shock of any type takes place (period 4), the efficiency of the DA and OTC mechanisms is very close. Mann-Whitney test in Table A.1 in the Appendix does not reject the null hypothesis of equal population medians between efficiency in DA and efficiency in OTC in period 4 (second column) for each of the four types of shock (D^-, D^+, S^-, S^+).

Differently from the DA market, in the OTC market the efficiency gap between the baseline and the negative shocks hangs over during periods 4–6 (−3.1 for D^- and −2 for S^-). As in the DA treatment, also the efficiency gap between the baseline and the positive shocks hangs over during periods 4–6 (+1.9 for D^+ and +3.3 for S^+). Notice that, if the positive shock concerns the supply function, then its positive effect on efficiency hangs over in periods 7–9 too (S^+ vs. no shock: +4.6 in periods 7–9). For all other shocks, reduced time length of trading periods 7–9 leads to a sharply decrease in the efficiency index, as it happens in the treatment without shock, with no significant difference in the efficiency index between shock vs. no shock treatments.

The following result can therefore be stated:

Result 5.a (Efficiency after shocks). Shocks that reduce (increase) the competitive quantity slightly decrease (increase) the efficiency of both the DA and the OTC market. In the long run, the efficiency gap with respect to the no-shock treatment presents the following trends: in the DA market, it vanishes for both types (demand and supply) of negative shock, and it hangs over for both types of positive shock; in the OTC market, it hangs over for all types of shock and increases only for a positive shock S^+ in the supply function.

Coming back to the comparison between efficiency in the DA market and in the OTC market, we have shown above that the introduction of a shock changes the main finding of Result 1 in the short run: after a shock, we observe a similar efficiency in the two markets in period 4. However, the main finding of Result 1 holds in the long run: Mann–Whitney test in Table A.1 in the Appendix rejects the null hypothesis of equal population medians between efficiency in DA and efficiency in OTC in periods 4–6 and in periods 7–9 for all types of shock (D^-, D^+, S^-, S^+). This is summarized in the following:

Result 5.b (Efficiency gap after shocks). The introduction of a shock offsets the efficiency gap between the DA and the OTC market in the period where the shock is applied: this is independent of the type of shock. However, the gap emerges again after few periods and increases as the length of the trading period shrinks.

The specific effect of a positive shock of the supply function over the efficiency of the OTC market deserves a more thorough discussion. Following the same procedure as in the previous section, we now analyze in more detail how the shocks applied in period 4 affect the traded quantity and the pattern of closing prices in the OTC market from period 4 onward. At the end of the section, we compare IM-inefficiency to EM-inefficiency in the OTC market.

Table 6 reports – for the first period of the second phase (i.e., period 4), on average over the second phase (periods 4–6), and on average over the third phase (periods 7–9) – the percentage of experimental sessions in which the traded quantity q in the OTC market is lower, equal or higher than the competitive quantity q^*, both without shocks (first line) and under each of the four types of shock.

We note that the treatments where the percentage of sessions with $q < q^*$ in period 4 is lower than in the baseline (i.e. no-shock) treatment are those characterized by an increase of the traded quantity (D^+ and S^+). However, the positive shock to the supply function S^+ consistently induces a lower percentage of sessions for which $q < q^*$ over all trading periods after the shock, i.e. both in the second phase (11.1% vs. 35.2% in periods 4–6) and in the last phase of the experiment (61.1% vs. 63% in periods 7–9). Furthermore, after S^+, the percentage of sessions with $q > q^*$ is higher than in the baseline treatment only for periods 4–6 and it tends to align to the baseline treatment in periods 7–9. Hence, the following result can be stated:

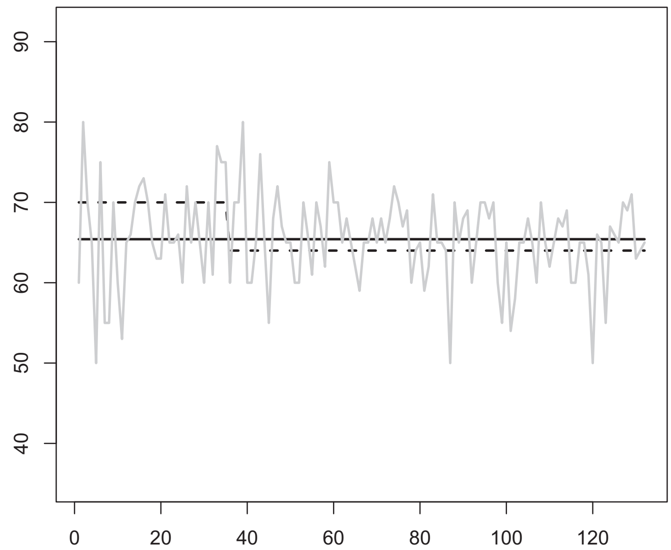

Fig. 4. Closing price patterns in an OTC treatment with shock S^+. Dashed line: competitive price; continuous line: average closing price.

Result 6 (Traded quantity after shocks in OTC). The introduction of a shock in the OTC market decreases the probability that $q < q^*$, and increases the likelihood that $q \geq q^*$ in the long run, only if the shock shifts downwards the supply function.

Table 6 also shows that the introduction of a positive shock of the demand function in the OTC market does not lead to any substantial difference – in terms of traded quantity – with respect to the no-shock treatment. To this phenomenon corresponds the fact that the OTC efficiency raises more significantly as a consequence of a S^+ shock than of a D^+ shock, as shown above in Table 5. The higher efficiency reached in the S^+ case can be explained by looking at the pattern of closing prices in the OTC market. In the previous section we pointed out that in the OTC market closing prices converge to a price below the competitive price p^*. The fact that a S^+ shock reduces the predicted competitive price p^* brings the value of p^* closer to the actual OTC closing prices, thereby raising the efficiency of this mechanism. Fig. 4 confirms this intuition. It presents the pattern of closing prices in an OTC market before (periods 1–3) and after (periods 4–9) a S^+ shock. The dashed line represents p^*, which in period 4 decreases as a consequence of S^+, while the continuous line represents the average closing price, which before the shock is below p^*.

The price pattern in Fig. 4 shows that, when p^* decreases as a consequence of an S^+ shock, the distance between the average closing price and p^* almost disappears. This happens because the predicted p^* decreases much more than the average closing price. In fact, buyers who are extra-marginal before the shock do not immediately realize (due to lack of public information in OTC about bids and asks) that they have become intra-marginal after the shock. We find that they accept closing prices slightly higher than the new equilibrium price. This corresponds to the above mentioned fact that, after the shock, the percentage of experimental sessions in which $q < q^*$ significantly decreases and the efficiency of the OTC mechanism increases. This effect cannot be produced by any of the other three types of shock. In fact, both S^- and D^+ increases p^*, thereby amplifying the gap between the average closing price and p^*. A D^- shock decreases p^*, but it also decreases $\bar{p}$ of a similar amount. In fact, sellers who are intra-marginal before the shock, do not immediately realize (due to lack of public information about bids and asks in OTC) that they are extra-marginal after the shock. We find that as soon as they realize they are not able to get rid of the unit of the good they own (same effect found in OTC with no shock) they ask for prices even lower than the average closing price before the shock. This is stated in the following result:

Result 7 (Closing price after shocks in OTC). A positive shock of the supply function S^+ decreases the competitive price p^* more than the average closing price $\bar{p}$. Given Result 3, this reduces the (positive) difference between p^* and $\bar{p}$. This effect is not found under any of the other three types of shock.

The above result can also be stated in terms of IM-inefficiency. In Section 4.1 we showed that the inefficiency of the OTC mechanism is also due to the failure of intra-marginal traders to exchange among themselves (IM-inefficiency), while this source of inefficiency is absent in the DA market. We also saw that IM-inefficiency occurs for sure when $q < q^*$. Since an S^+ shock drastically reduces the cases in which $q < q^*$ in OTC markets (Table 6), we conclude that this type of shock also reduces the IM-inefficiency of the OTC mechanism, thereby raising its overall efficiency. This is confirmed by the regression analysis of efficiency and IM-inefficiency by treatment (see Table A.3 in the Appendix): In the OTC treatment, the dummy variable for the S^+ shock type has a significant negative impact (*P-value* = 0.064) over the IM-inefficiency. Notice that in the OTC treatment none of the other three shocks has a significant impact either over the market efficiency or the sources of market inefficiency.

Our regression analysis seems to point out also that, in the DA treatment, shocks to the supply curve tend to increase market efficiency (although not significantly) from the baseline level of efficiency. On the contrary, shocks to the demand curve leave the market completely unaffected. Along the same lines, the trade-off between IM and EM inefficiencies does not change after the market has suffered a shock. The latter result is not surprising, since the institutional framework of the DA market allows it to absorb shocks quite rapidly.

We can now state the last result of our research:

Result 8 (Sources of inefficiency after shocks). The only shock that significantly affects efficiency in the OTC market in the long run is a positive shock of the supply function S^+. Efficiency increases with respect to the no-shock treatment thanks to a significant reduction in intra-marginal inefficiency. In the same fashion, only shocks to the supply function affect efficiency in the DA market, although they do not have any impact on the sources of market inefficiency.

5. Summary and conclusions

OTC trading mechanisms are economically relevant because in many markets, such as those where currencies, real estate, bulk commodities and certain types of bonds are traded, negotiations and transactions occur on a private, bilateral basis. Despite their importance, OTC mechanisms have attracted less attention than other, more centralized trading mechanisms, such as auctions. As a consequence, the study of the functioning and performance of OTC trading mechanisms is still inchoate. While Duffie and his co-authors have studied OTC markets from a theoretical viewpoint by advancing formal models for a number of OTC markets, in this paper we have attempted to clarify the working of OTC markets by an experimental approach.

More precisely, we designed an OTC mechanism in which each agent looks for the best counterpart through private bids and asks submitted via a networked computer. In a series of classroom experiments without monetary rewards that involved more than 3300 undergraduate students, we studied the features and performance of this electronic OTC mechanism by taking as a benchmark an electronic DA mechanism. The main difference between the two mechanisms is informational in nature: while the DA market is characterized by both pre-trade and post-trade transparency, in the OTC markets only post-trade transparency is implemented. We examined how this gap in the available public information affected the functioning of the OTC trading mechanism, and to what extent it reduced the efficiency of the OTC market as compared to the efficiency of the DA market. To the best of our knowledge, our paper is the first that investigates electronic OTC markets from an experimental perspective.

We found that the loss of public information that characterizes our OTC market with respect to a DA market reduces the efficiency of the OTC mechanism by almost 8 efficiency points (Result 1). We also showed that this loss of efficiency is associated with two facts. First, in more than half of the trading periods the quantity actually traded in OTC markets is lower than the competitive quantity. As subjects become more familiar with the OTC mechanism the quantities actually traded increase, but this learning effect weakens when the trading period becomes shorter (Result 2). Second, in the OTC mechanism the average price at which the commodity units are traded is significantly lower than the competitive price (Result 3). We then discovered that, while the only source of inefficiency in DA markets is extra-marginal inefficiency (i.e., extra-marginal traders who exchange with intra-marginal traders), in OTC markets inefficiency is also of the intra-marginal type. That is, there are some intra-marginal traders who could not exchange their good because of the lack of public information characterizing the OTC mechanism (Result 4).

In the second part of the paper we introduced shocks into the picture, i.e., shifts in either the demand or the supply curve that modify the competitive equilibrium, and studied how efficiency is affected by different types of shocks. We found that, in the period when the shock takes place, the efficiency gap between the DA and the OTC mechanism shrinks. This result is independent of the type of shock. However, the gap emerges again after a few periods and increases as the length of the trading period decreases (Result 5.a and 5.b). Finally, we discovered that the only shock that significantly affects the functioning and efficiency of the OTC mechanism even in the long run is a positive supply shock, that is, a downward shift of the supply function that increases the competitive quantity and decreases the competitive price. This type of shock, in fact, decreases the cases in which the quantity actually traded in OTC markets is lower than the competitive quantity (Result 6); it reduces the difference between the competitive price and the average closing price in OTC markets (Result 7); and it also reduces the intra-marginal inefficiency associated with the OTC mechanism and thus increases its efficiency (Result 8).

From a policy perspective, these results suggest that regulators of financial and other markets in which interactions take place via computer and negotiations occur on a bilateral basis should prefer DA allocation mechanisms over OTC mechanisms. In fact, DA mechanisms warrant higher information disclosure and thus market equilibria that are more consistent with the competitive one. If an OTC mechanism is in place and for some reason it cannot be substituted by a DA mechanism, regulators should give OTC traders more time to learn how the mechanism works than would be the case in a DA market. Regulators should also give traders in an OTC market a sufficiently extended time to negotiate with other traders and find out their best counterpart. Our experiment indicates, in fact, that too short transaction periods affect negatively and in a significant way the efficiency of OTC markets. Also in the presence of unexpected modifications in the economic environment, which in our setting take the form of exogenous shocks, the DA mechanism seems to perform better than the OTC mechanism. Finally, if regulators are mainly concerned with enforcing a market mechanism that reveals a price very close to the competitive equilibrium, the DA market ought to be preferred. In particular, this work shows that prices in the OTC market are generally lower than the competitive equilibrium price, mainly because of the persistent selling pressure: when public information about existing bids and asks is not available, sellers feel much more pressure than buyers to find a trading counterpart. This in turn leaves room for positive surplus for buyers who would be excluded from transactions if the competitive equilibrium were obtained. Hence, if an OTC mechanism is implemented, regulators should protect more (and eventually compensate) intra-marginal sellers, particularly those with costs closer to the equilibrium price.

One may legitimately ask why OTC markets are so widespread given that they are less efficient than DA markets. Duffie (2012, pp. 6–8) suggests that in a number of cases, such as for certain types of collateralized debt obligations, the traded commodity is so peculiar and the traded volumes so small that it is difficult to implement trading mechanisms different from OTC. In other cases, where the traded commodity is sufficiently standardized and the traded volumes sufficiently large, dealers, brokers and other intermediating traders who profit from the opacity of the OTC markets may block the implementation of market institutions more transparent than OTC. However, at the moment we do not have a single convincing explanation of why OTC markets are so widespread.

These policy considerations are admittedly very tentative, not least because our paper seems to be the first systematic investigation of an electronic OTC mechanism from an experimental perspective. There is in fact ample room for further studies that explore both theoretically and experimentally the properties of this economically relevant, yet still opaque, market institution.

Appendix

Table A1
Mann Whitney U-statistics for the difference in efficiency between DA and OTC (*P-values* in brackets).

	Period 4	Periods 4–6	Periods 7–9	Periods 1–9
No Shock	231.5	1959.5	2376.0	20084.5
	(0.028)	(0.002)	(0.000)	(0.000)
D^-	16.0	220.5	248.0	2169.0
	(0.809)	(0.065)	(0.007)	(0.000)
D^+	21.0	233.0	268.0	2249.0
	(0.686)	(0.025)	(0.001)	(0.000)
S^-	22.0	247.0	291.0	2463.5
	(0.574)	(0.007)	(0.000)	(0.000)
S^+	20.5	235.5	263.0	2029.5
	(0.739)	(0.018)	(0.001)	(0.000)

Table A2
Dynamic Panel Data regressions of closing prices over all periods (*P-values* in brackets).

	DA	OTC	*Joint*
Lag price	0.355	0.315	0.335
	(0.000)	(0.000)	(0.000)
Buyer V	0.278	0.256	0.267
	(0.000)	(0.000)	(0.000)
Seller C	0.315	0.381	0.346
	(0.000)	(0.000)	(0.000)
Treatment			-0.691
			(0.000)
Sargan test	0.000	0.000	0.000
AB test 1	0.000	0.000	0.000
AB test 2	0.000	0.001	0.000
Wald test	0.000	0.000	0.000

Table A3
Beta regressions of efficiency and intra-marginal (IM) inefficiency by treatment over all trading periods (*P-values* in brackets). Control variables for market period not reported.

	DA		OTC	
	Efficiency	IM-inefficiency	Efficiency	IM-inefficiency
Intercept	2.409	−1.950	2.285	−0.699
	(0.000)	(0.001)	(0.000)	(0.000)
$(q - q^*)$	0.154	−0.661	0.250	−0.529
	(0.000)	(0.000)	(0.000)	(0.000)
$\|\bar{p} - p^*\|$	−0.038	−0.076	0.010	0.000
	(0.052)	(0.115)	(0.453)	(0.980)
D^-	−0.145	0.322	0.018	−0.024
	(0.226)	(0.326)	(0.852)	(0.858)
D^+	0.080	0.296	0.079	−0.062
	(0.517)	(0.536)	(0.417)	(0.643)
S^-	0.177	0.399	0.085	−0.049
	(0.156)	(0.267)	(0.385)	(0.720)
S^+	0.120	0.181	0.107	−0.267
	(0.339)	(0.569)	(0.288)	(0.064)

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.socec.2016.03.003.

References

Ashcraft, A.B. and D. Duffie, 2007. "Systemic illiquidity in the federal funds market." American Economic Review 97(2), 221–225.
Attanasi, G., S. Centorrino, and I. Moscati, 2016. "Zero-intelligence and human agents in an experimental over-the-counter market." Proceedings of the 2014 LABSI Workshop, University of Siena: Mimeo.
Bardsley, N., R. Cubitt, G. Loomes, P. Moffatt, C. Starmer, and R. Sugden, 2009. Experimental Economics: Rethinking the Rules. Princeton, NJ: Princeton University Press.
Blundell, R. and S. Bond, 1998. "Initial conditions and moment restrictions in dynamic panel data models." Journal of Econometrics 87(1), 115–143.
Camerer, C. and R. Hogarth, 1999. "The effects of financial incentives in experiments: a review and capital-labor-production framework." Journal of Risk and Uncertainty 19(1), 7–42.
Cason, T.N. and D. Friedman, 1996. "Price formation in double auction markets." Journal of Economic Dynamics and Control 20, 1307–1337.
Cason, T.N. and D. Friedman, 2008. "A comparison of market institutions." In Plott, C.R. and V.L. Smith (Eds.), Handbook of Experimental Economics Results. 264–272 Amsterdam, New York: North Holland.
Chamberlin, E.H., 1948. "An experimental imperfect market." The Journal of Political Economy 56(2), 95–108.
Davis, D.D., G.W. Harrison, and A.W. Williams, 1993. "Convergence to nonstationary competitive equilibria: an experimental analysis." Journal of Economic Behavior & Organization 22(3), 305–326.
Duffie, D., 2010. "Asset price dynamics with slow-moving capital." The Journal of Finance 65(4), 1237–1267.
Duffie, D., 2012. Dark Markets: Asset Pricing and Information Transmission in Over-the-Counter Markets. Princeton, NJ: Princeton University Press.
Duffie, D., N. Gârleanu, and L.H. Pedersen, 2005. "Over-the-counter markets." Econometrica 73(6), 1815–1847.
Duffie, D., N. Gârleanu, and L.H. Pedersen, 2007. "Valuation in over-the-counter markets." Review of Financial Studies 20(6), 1865–1900.
Duffie, D., G. Giroux, and G. Manso, 2010a. "Information percolation." American Economic Journal: Microeconomics 2(1), 100–111.
Duffie, D., S. Malamud, and G. Manso, 2009. "Information percolation with equilibrium search dynamics." Econometrica 77(5), 1513–1574.
Duffie, D., S. Malamud, and G. Manso, 2010b. "The relative contributions of private information sharing and public information releases to information aggregation." Journal of Economic Theory 145(4), 1574–1601.
Duffie, D., S. Malamud, and G. Manso, 2014. "Information percolation in segmented markets." Journal of Economic Theory 153, 1–32.
Duffie, D. and G. Manso, 2007. "Information percolation in large markets." American Economic Review 97(2), 203–209.
Feldhütter, P., 2012. "The same bond at different prices: identifying search frictions and selling pressures." Review of Financial Studies 25(4), 1155–1206.
Fischbacher, U., 2007. "z-Tree: Zurich toolbox for ready-made economic experiments." Experimental Economics 10(2), 171–178.
Friedman, D. and J.P. Rust (Eds.), 1993. The Double Auction Market: Institutions, Theories, and Evidence. Reading, MA: Addison-Wesley.
Gode, D.K. and S. Sunder, 1993. "Allocative efficiency of markets with zero-intelligence traders: market as a partial substitute for individual rationality." The Journal of Political Economy 101(1), 119–137.
Guala, F., 2005. The Methodology of Experimental Economics. Cambridge, UK: Cambridge University Press.
Hendershott, T. and A. Madhavan, 2015. "Click or Call? Auction versus search in the over-the-counter market." The Journal of Finance 70(1), 419–447.
Holt, C.A., 1996. "Classroom games: trading in a pit market." The Journal of Economic Perspectives 10(1), 193–203.
Holt, C.A., 1999. "Teaching economics with classroom experiments." Southern Economic Journal 65(3), 603–610.
List, J.A., 2002. "Testing neoclassical competitive market theory in the field." Proceedings of the National Academy of Sciences 99(24), 15827–15830.
List, J.A., 2004. "Testing neoclassical competitive theory in multilateral decentralized markets." Journal of Political Economy 112(5), 1131–1156.
Ospina, R. and S.L. Ferrari, 2012. "A general class of zero-or-one inflated beta regression models." Computational Statistics & Data Analysis 56(6), 1609–1623.
Plott, C.R., 2008. "Properties of disequilibrium adjustment in double auction markets." In Plott, C.R. and V.L. Smith (Eds.), Handbook of Experimental Economics Results. 16–21 Amsterdam, New York: North Holland.
Rust, J., J. Miller, and R. Palmer, 2008. "Behavior of trading automata in a computerized double auction market." In Friedman, D. and J.P. Rust (Eds.), The Double Auction Market: Institutions, Theories, and Evidence, 155–198. Reading, MA: Addison-Wesley.
Smith, V.L., 1962. "An experimental study of competitive market behavior." The Journal of Political Economy 70(2), 111–137.

Giuseppe Attanasi is Associate Professor of Economics and Director of the Laboratory of Experimental Economics at University of Strasbourg. His research focuses on behavioral decision making, game theory and experimental economics. His work has appeared in *European Economic Review, International Game Theory Review, Journal of Behavioral and Experimental Economics, Journal of Economic Psychology, Management Science, Marketing Letters, Organizational Behavior and Human Decision Processes, Pacific Economic Review*, and *Theory and Decision*.

Samuele Centorrino is an Assistant Professor of Economics and member of the Center for Behavioral Political Economy at Stony Brook University, where he has joined the faculty in August 2014. His research interests include theoretical econometrics, and experimental economics, with a special focus on trust and cooperation. His work has appeared in *Evolution and Human Behavior*, and *Journal of Behavioral and Experimental Economics*.

Ivan Moscati is Associate Professor of Economics at the University of Insubria, Varese, Italy, and teaches History of economics at Bocconi University, Milan. His research focuses on the history and methodology of microeconomics, with a special focus on decision analysis and experimental economics. He is an associate editor of the *Journal of Economic Methodology*, and his work has appeared in *History of Political Economy, Economia Politica, European Journal of the History of Economic Thought, Journal of the History of Economic Thought*, and *Journal of Economic Methodology*.