The Impact of a Pre-Opening Session on Subsequent Trading: an Experimental Analysis

Caferra, Rocco and Morone, Andrea and Nuzzo, Simone

Università degli Studi di Bari "Aldo Moro"; Dipartimento di Economia, Management e Diritto dell'Impresa Università degli Studi di Bari Aldo Moro. Largo Abbazia Santa Scolastica, 53 70124 Bari (Italy)

19 March 2019

The Impact of a Pre-Opening Session on Subsequent Trading: an Experimental Analysis

Rocco Caferra [a], Andrea Morone [b] , Simone Nuzzo [c] *

[a] rocco.caferra@gmail.com

[b] a.morone@gmail.com

[c] snuzzo1@gmail.com

Abstract

The purpose of this paper is to examine the market structure at the opening and its influence on subsequent trading. In particular, we measure the market efficiency of a pre-opening call market (CM) followed by a continuous double auction (CDA) focusing on the role of information. Aimed by Weigelt (1991), Theissen (2000) and Hinterleitner at al. (2015) we check whether the introduction of a call market leads to underreaction among agents' bids, improving market efficiency. Results evidence a positive correlation between pre-opening price and subsequent prices traded and a lower price-dividend deviation in case of high quality information.

1 Introduction

A growing body of literature addressed his study on the role of information on market efficiency and price formation, evaluating the impact of the trading institute.
Information is essential in financial market, where individuals often act on the basis of their own private information and a public knowledge about the behaviour of the others (Banerjee and Bikhchandani et al., 1992). One the one hand, Grossman and Stiglitz (1976) and Plott and Sunder (1982) studied the dissemination of information finding that price converge toward the equilibrium simply by observing market phenomena,on the other a widespread branch of economists focused on the importance of market micro-structure in the price

*Università degli Studi di Bari "Aldo Moro"; Dipartimento di Economia, Management e Diritto dell'Impresa Università degli Studi di Bari Aldo Moro. Largo Abbazia Santa Scolastica, 53 70124 Bari (Italy).

discovery mechanism, indeed Schinitzlein (1996) stated that "the discussion of the costs and benefit of insider trading should take place within the context of a specific market". The continuous double auction (CDA) and the single call market (CM) have been the two most analyzed trading mechanisms in literature. Smith (1982) found the price convergence process to be more rapid in the continuous double action, conversely Morone and Nuzzo (2016) noticed the persistence of informational mirages in both the trading systems, while Hinterleitner et al (2015) combined the two form of markets, detecting that a call-auction in the market pre-opening phase does have a positive spillover effect in term of spread, volatility and trading volume.
Our paper contributes to the existing literature by analyzing the effect that the introduction of a pre-opening call market before a continuous double action has on the main financial market stylized fact. This work is organized as follows: Section 2 reviews the actual state of art, Section 3 describes the Experiment design,Section 4 offers a deeper analysis of the empirical outcomes and Section 4 concludes.

2 Literature Review

Information has always played a crucial role both in market and non-market context. As outlined in Banerjee (1992) and Bikhchandani et al. (1992), herd behaviour may result from private information not publicly shared, indeed both of these papers showed that individuals, acting sequentially on the basis of private information and public knowledge about the behaviour of others, may end up choosing the socially undesirable option. In market conditions, Grossman and Stiglitz (1976) showed that uniformed traders can become informed through the price in such a way that private information is aggregated correctly and efficiently. Earlier studies of Fama (1965) revealed a market is efficient whenever prices fully reveal the available information. Nevertheless, it is equally true that prices converge properly in some, but not in every cases. In fact, there is no reason to suppose that agents are aware about the true value of the dividend of the traded asset, conversely it is more plausible that they correct their prior belief by means of the signals they received from the market (Rational Expectation Hypothesis). For this reason, the impact of the informational distribution on market quality and their relation with the market micro-structure has been continuously investigated in literature. Real-life markets leaves little rooms to the proper identification of traders behavior, failing to check relevant characteristics, noised by external circumstances that could not be under control, although the recent developments of experimental procedures provide the advantage of reproducing the market environment in a laboratory area, where powerful control for all significant variables becomes possible.
Guala and Mittone (2007) tackled this aspect arguing that many experiments are not aimed at a well-specified real-world target but contribute to a "library" of robust phenomena. Previously, Roth (1986,1988,1995) proposed a three-fold classification that moves from a pure theorist approach from a policy-maker

support perspective. The supporting idea is that a laboratory setting allows to check for robustness in variables changes, all other things being equals, highlighting a cause-effects linkage. This is why the aim of this paper is to find evidences and differences due (or strictly related) to a change in the experimental design, contributing to the exiting "library" of phenomena which can be exploited by policy maker. Our starting point is the identification of a theoretical framework which properly match with observed phenomenon, which is why we exploit a Bayesian approach that is jointly based both on theoretical and empirical evidence (see next section for more details). A great number of experimental studies involved continuous double auction market (CDA) as a benchmark for testing the performance of other institutions (e.g. Ketcham et al., 1984 and Horung et al., 2014). In this context, several paper focused on the issue of aggregation of different pieces of information owned by different traders and its dissemination. Plott and Sunder (1982) analyzed the information distribution concluding that traders infer the state of the world by simply observing market events, while Hey and Morone (2004) found that misinformed agents acting on their private information mislead the market, although the volatility of prices is lower when the quality and quantity of information in the market are higher. Furthermore, Huber et al. (2008) observed that a positive relationship between information and higher profits was detected only for very high levels of information. Lux et al. (2016) analyzed different level of signal diffusion, finding that treatments in which information distribution is bimodal (i.e. there are both informed and uninformed traders) bring about higher informational efficiency than treatments where information is uniformly distributed.

The convergence towards the theoretical prediction is doubtless a quality hint and the experimental framework provides the opportunity to follow the price path during the whole time frame. Pioneering studies about the approximate convergence have been made by Smith (1962) and replicated by Sunder (1995) and Morone (2008), evidencing a close connection between information reliability and price fluctuation around its fundamental value.

Price noises lead to indeterminacy in the equilibrium of the dynamics and this directly influence the exchange returns. Mandelbrot and Fama (1963) estabilished that changes in asset price returns do not have a normal distribution, because of the influence of the outliers (i.e. both extreme favorable and unfavorable trading) at the tail of the distrbutions. "Fat tail distribution" (Bouchaud 2001) is an undesiderable outcome in finance because it both affects the calculation of the expected return and reflects both inequalities and bias in the information distribution, as widely demonstrate in literature (e.g. Morone (2008)).

In this context, trading institutions have to lay down the basis for a transparent and efficient trading mechanism, solving the "incentive, coordination and logistical problems associated with price formation and exchange" (Cason and Friedman, 1996). The objective of a policy-maker is to determine which market structure is ideal for trading. With regard to the market structure, Theissen (2000) compared continous double auction, call market and dealer market. In her contribution the call market showed a significant tendency to underreact to the arrival of new information, maybe the continous auction and the dealer market exhibited fewer deviation from the true value of asset. Morone and Nuzzo (2016) combined these aspects comparing the performance of a call market and a continous double auction, restating the design of Camerer and Weigelt (1991) where the presence of insider is expressed in terms of probability. They found that none of trading mechanism outperforms on the other and the only appreciable advantage of call markets is a significant reduction of price volatility when no inside information has entered the market. Both Madhavan (1992) and Shnitzlein (1996) found that a call auction structure is best suited in terms of informational efficiency and liquidity. This is why in recent times most western capital markets have introduced a call auction as their opening mechanism. As widely demonstrated in Hinterleitner et al. (2015) contribution, an opening call auction prior to continuous trading leads to a smaller opening price deviation from fundamental value and lower spreads than a continuous double auction alone.

Inspired by the current state of art, we aim to examine the relevant characteristics of this hybrid form of market: Does a pre-opening call market (CM) followed by a continuous double auction (CDA) ameliorate market efficiency? Actually, inefficiencies are strictly linked to traders' beliefs and their failures in updating correctly their prior knowledge. In a double auction mechanism, where private signals instantaneously become public, they find fertile ground to flourish. We hypothesize, according to earlier studies, that a pre-opening call market could lessen the overreaction of agents and speed up price convergence toward the real value of the fundamental.

In our laboratory framework we recall the model of herd behaviour of Bikhchandani et al. (1993), indeed agents acted sequentially on the basis of their own signal and the information spread out by other subjects' guesses. We introduce different level of information both in its distribution and in its accuracy, hence a general state of uncertainty is perceived and report the results by comparing the observed prices traded with different market predictors.

3 Experimental Design

The experiment was conducted at the LEE laboratory at University of Jaume I and programmed in z-Tree (Fischbacher 2007). A total of 144 agents traded a one-period life asset in 18 independent markets (three for each market institute combined with the relative treatment), grouped in a within-group design of 8 traders per market.

At the beginning, each agent was provided with 200 units of experimental money and 10 units of the asset. There was a common uncertainty about the state of the world: at the end of each trading session the dividend might assume a value of either 20 (Good State) and 10 (Bad State) with an equal degree of probability given by the flip of a coin in each trading session. During the "hybrid" treatment each trading period was divided into two parts: a one-minute pre-opening call market (CM) followed by a four-minute continuous

double auction (CDA); conversely the other treatment was given by a stand-alone four-minute CDA trained in each period. The trading activity in each market layed down over 7 trading periods. There were two practice periods at the beginning of the session.
Uncertainty about the dividend value is expressed both in terms of accuracy and distribution, hence we have six types of treatment summarized in the table 1.
Earnings were expressed in Experimental Currency Unit (ECU) and they were converted in Euro at the exchange rate of 1 ECU to 0.005. Agents were informed about their profits and the dividend value at the end of each period, however they received the payment at the end of the session as a cumulative sum of the profits of the 7 real periods. They could sell no more than the asset they owned and buy no more than they could afford on the basis of the money in their portfolio. In our experiment traders earned, on average, 10 euros per hour. The trading institutions can be described as follows.

	Precision	Distribution	# of Signals
Treatment 1	6/8	4/8	16(8)
Treatment 2	6/8	2/8	32(8)
Treatment 3	6/8	8/8	8 (8)
Treatment 4	5/8	4/8	16(8)
Treatment 5	5/8	2/8	32(8)
Treatment 6	5/8	8/8	8 (8)

Table 1: Summary table, In case of polarized information (treatment 1,2,4,5) each informed agent receives more than 1 signal (2 in 1-4 and 4 in 2-5).

Pre-opening mechanism consisted in a call market (CM) where each trader privately submitted his purchase or sale order. For a single unit of the asset, the purchase order was the highest acceptable purchase price and the sale order represented the lowest acceptable sale price. When the trading sub-period was closed, all the orders previously submitted were collected and processed. In particular, purchase orders were ordered from the highest to the lowest and the demand function was derived. Sale orders were instead ordered from the lowest to the highest and the supply function was derived. The intersection point of the demand and supply function determined the clearing price at which the orders were executed. Nevertheless, there was no guarantee for all the submitted orders to be executed. In particular, only the purchase orders at a price equal to or above the clearing value and only the sale orders at a price equal to or below the equilibrium value were executed. Then, the clearing system provided the market with a uniform price for each call.
The clearing price was the opening price of the subsequent continuous double auction (CDA), where subjects , at any moment during the trading period, were free to enter a bid (an offer to buy one unit of the asset for a specific amount of cash) or a request (an offer to sell one unit of the asset for a specific amount of cash). As a trade proposal was submitted, it appeared on the book and became public. Traders could accept outstanding bids and asks. As an existing bid or ask was accepted by another trader, a transaction was

completed and the price at which the contract had been closed also appeared on the book and become public information. Traders could buy/sell one unit at a time and as often as they want in each trading period. For these reasons, this trading institution is the richest one in terms of within period information and trading opportunities. Otherwise, the stand-alone CDA treatment follows the same rule of the one in the hybrid form.

3.1 Theoretical Framework and Hypothesis Set

By exploiting the Bayesian inference, we can compute the probability that the true state of the world might occur (Alfarano, Camacho and Morone, 2010) . Let us define :

- D=$\{d_1,d_2\}$ =$\{10,20\}$ as the set of possible pay-offs;
- I=$\{10,20,0\}$ as the informational set, where $I_I = \{10,20\} \subset I$ and $I_N = \{0\} \subset I$ define respectively the informative and uniformative signal subsets;
- p as the probability that an informative private signal is correct (it might be either $\frac{6}{8}$ and $\frac{5}{8}$
- q=1-p as the probability that an informative private signal is incorrect;
- f as the probability to infer correctly on an uniformative signal;
- k_1, k_1,k_3 and k_4 as the number of inferences made on informative and informative signal by assuming agents' rationality, with k_1+k_1+k_3+k_4 =N;

The basic idea is that those who do not receive a signal infer that the two dividends are equally likely to occur (hence k_3=k_4), becoming neutral in undermining the market probability of success.
Theoretically speaking, we have that :

$$Posterior \propto Prior \times Inference$$

and a binomial model best fits our case, which is why we can assume a beta distribution both for the prior and the inference model.
As stated by the principle of indifference [1], a prior which can not give any type of evidence in favor of one specific result has to be modeled as a uniform distribution where all the events are equally likely to occur. This is why, we model our prior as:

$$Beta_{prior} = Beta(\theta; \alpha, \beta) = \frac{1}{B(\alpha, \beta)} \theta^{\alpha-1} (1-\theta)^{\beta-1}$$

[1]see Keynes, John Maynard (1921). "Chapter IV. The Principle of Indifference". A Treatise on Probability. 4. Macmillan and Co. pp. 41–64

Where θ is the probability to observe the dividend and α and β are scale parameters. It can be proved that, if α and β are equal to 1, we get a uniform distribution. In fact:

$$E(\theta|\alpha = 1, \beta = 1) = \int_0^1 \theta f(\theta|\alpha,\beta)d\theta = \int_0^1 \frac{1}{B(\alpha,\beta)}\theta\theta^{\alpha-1}(1-\alpha)^{\beta-1}d\theta$$

with

$$B(\alpha,\beta) = \int_0^1 \theta^{\alpha-1}(1-\alpha)^{\beta-1}d\theta$$

By substituting α and β we have:

$$B(\alpha,\beta) = \int_0^1 \theta^{\alpha-1}(1-\alpha)^{\beta-1}d\theta = \int_0^1 \theta^0(1-\alpha)^0 d\theta = [\theta]_0^1 = 1$$

and

$$E(\theta|\alpha = 1, \beta = 1) = \int_0^1 \theta(1-\alpha)^0 d\theta = \left[\frac{\theta^2}{2}\right]_0^1 = \frac{1}{2}$$

Which means that both of the events are equally probable.
Moving onwards, we have that[2]:

$$Beta_{Posterior} \propto Beta_{Prior} \times Beta_{Inference} = 1 \times Beta_{Inference} = Beta_{Inference}$$

hence prior does not influence the calculus of probability distribution.
By applying the same condition, we can state that uninformative signals do not affect the calculus of the joint posterior distribution. Now, these principle might be applied to our data.

According to the type of treatment, p might be either $\frac{6}{8}$ and $\frac{5}{8}$. Setting q=1-p, we can model the following Bayesian rule (given 20 as the dividend drawn at the end of the trading session) :

$$Pr(D = 20|I) = \frac{Pr(D = 20) \times Pr(I|D = 20)}{Pr(I)}$$

A priori, Pr(D=20) is equal to $\frac{1}{2}$ because events are equally likely to occur, Pr(I|D=20) is the probability of success given from the inference on the observed signal and Pr(I) is the marginal distribution of the informational set according to the probability to observe dividends (Pr(I)=Pr(D=20)× Pr(I|D=20)+Pr(D=10)× Pr(I|D=10)). In order to demonstrate the neutrality of the uninformed trader on the calculus of the Bayesian Efficient Price, we state that they infer that the two events are equally probabily. Given k_1, k_1,k_3 and k_4 as the number of inference made on correct,uncorrect and neutral (both k_3 and k_4) signals (with k_1+k_1+k_3+k_4 =N) we have:

$$Pr(D = 20|I) = \frac{\frac{1}{2}\binom{N}{k_1,k_2,k_3,k_4} \times p^{k_1}q^{k_2}f^{k_3}(1-f)^{k_4}}{\frac{1}{2}\binom{N}{k_1,k_2,k_3,k_4} \times p^{k_1}q^{k_2}f^{k_3}(1-f)^{k_4} + \frac{1}{2}\binom{N}{k_1,k_2,k_3,k_4} \times p^{k_2}q^{k_3}f^{k_3}(1-f)^{k_4}}$$

[2]The result comes from the following simplification :$\frac{1}{B(\alpha,\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}$=1 if α=β=1 for each value of θ.

Where k_3 is equal to k_4, since the probability to infer that the signal is 20 or 10 from an uninformative signal the same number of time. Hence, by applying the exponential property, f is $1/2$ and f+1-f =1, hence it vanishes in the calculus of the probability of success:

$$Pr(D = 20|I) = \frac{p^{k_1}q^{k_2}}{p^{k_1}q^{k_2} + p^{k_2}q^{k_3}}$$

After some algebra we have:

$$Pr(D = 20)|I) = \frac{1}{1 + \frac{q}{p}^{2k_1-(k_1+k_2)}}$$

Hence we can state that the probability to observe the right dividend by inferring on the data is not a function of unobserved signals.
We consider the Pre-Opening price in CMDA treatment as a public signal but we can not say to what extend is reliable. This is why, as a null hypothesis of our research, we treat it as a neutral signal that do not influence the probability to trade close to the dividend. Therefore, we aim to reject this hypothesis by evidencing that agents incorporate it in their choices.
To wit, if we consider that in the hybrid treatment subjects play the call market at period n and the double auction at $n+1$, we can model the following Dynamic Bayesian rule:

$$P_{n+1}(D = d_1|I_t) \propto P(D = d_1) \times P_{n+1}(I_t|D = d_1)$$

Given the likelihood of the DA treatment as $P(I_t|D = d_1)$, our hypothesis can be explained as:

$$P_{n+1}(I_t|D = d_1) \neq P(I_t|D = d_1)$$

the study of the direction of possible inequality is worthy of attention. Now we can calculate the Bayesian Efficient Price as:

$$BEP = Pr(D = 20|I) \times 20 + Pr(D = 10|I) \times 10$$

That is, the probability to observe the dividend is not merely given by the average quality of information present in the market, maybe it is a function of the number of time each information type appear. Theoretically speaking, given the highest number of correct signal disseminated, we can infer that agent might be able to recognize the true dividend in each type of treatment. The unique aspect that might slower the convergence is the different levels of uniformed traders.
Given the aforementioned consideration, we introduce the following market predictions:

- Dividend (D)

- Bayesian Efficient Price (BEP): BEP= Pr(D=d_1|I)×d_1+Pr(D=$d_2|I)\times d_2$
- Efficient Price (EP): $EP = \sum_i \frac{I_i}{N}$, where i defines the i_{th} inference made.[3]

It can be noticed that the Bayesian Efficient Price converge toward the dividend, that is the best guess an agent can infer, while the standard efficient price come from the Expected Utility theory as a weighted average of the possible events.
In our experimental design there are no insiders, then there are no perfectly informed agents and even if in some periods only few agents are informed, their signal is expressed in probability terms.
Since there is no certainty about the true state of the world,a price convergence towards the dividend is expected *if and only if* subjects correctly infer on private signals revealed by others. In other words, a Bayesian approach suggests that, once private signal are publicly shared there is a positive spillover and other subjects can perceive the forthcoming dividend, inasmuch as correct information are higher in number [herd behaviour]. On the other hand it could happen that the uninformed subjects are influenced by those who have the wrong signal, bringing to an undesiderable outcome. In case of risk neutrality, the subjects can individually weigh each of the signals received and therefore the market price will be the average of the information collected (Efficient Price).
Given the aforementioned consideration, we aim to analyze the main financial stylized facts.

- **Hypothesis 1** : Market efficiency differs according to market structure. We measure Market Efficiency on the basis of the three benchmarks listed before. In particular:

  - $DD_{jp} = \sum_t \frac{|p_{jpt} - D_{jp}|}{T}$ is the dividend deviation;
  - $DBEP_{jp} = \sum_t \frac{|p_{jpt} - BEP_{jp}|}{T}$ is the bayesian efficient price deviation;
  - $DEP_{jp} = \sum_t \frac{|p_{jpt} - EP_{jp}|}{T}$ is the efficient price deviation.

  where j,p and t define respectively the market code, the trading period and the subsequent number of exchange. Hence we have an aggregate measure at a market level for each trading period.
  Hinterlenter el alii (2015) discovered improvements in volatility and quantity traded in the CMDA institute, then we also review these aspects.
  Morevorer, Plott and Sunder (1982) found that when agents replicated the same task over time, markets' behaviour converged toward the equilibrium. Price convergence has a twofold meaning: it is a market quality signal and at the same time it is a measure of the agents' ability to learn. We check whether we might reject unit root hypothesis in each trading period. Furthermore, we might evidence whether or not agents treat

[3]We consider the uninformed price (15) as the signal received by uninformed traded.

pre-opening price as an uninformative signal or they include it in their choice.

- **Hypothesis 2** : The “fat tails” phenomenon of the financial returns is different in CMDA.
The underlying idea is that whether there will be an improvement of the informative efficiency it can be seen an alignment of subjects’ expectations and therefore a reduction both of the volatility of the returns and of the consequent probability to obtain extra profits. This can be measured considering both the kurtosis of the distribution- where if the distribution has average in zero it would mean an increase of the exchange around the same price- and the analysis of the "heavyness of the tails" to check excessive deviations in the exchanges (i.e.returns higher than the value expected from a normal distribution).

4 Analysis and Results

Some examples of trading activity are reported in figure 1 (see the appendix for the full representation). The x axis tracks time in seconds and the y axis represents the price traded (in black), the pre-opening information (in green) and the dividend (in dark red), while the quantity traded is simoultaneously shown in the subplot.

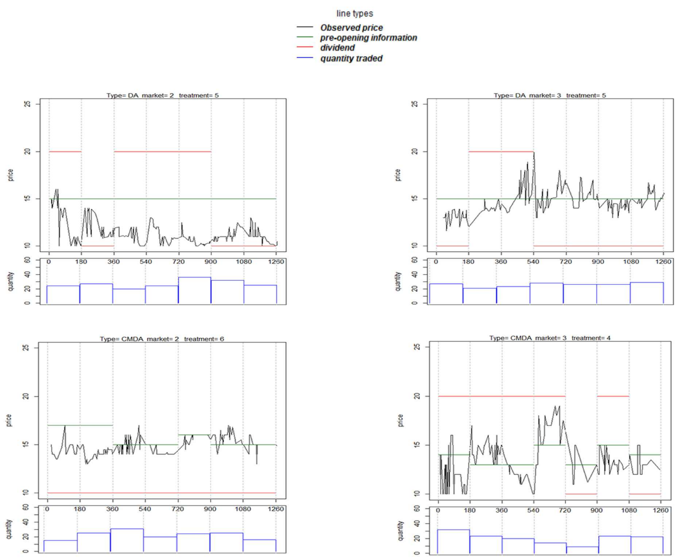
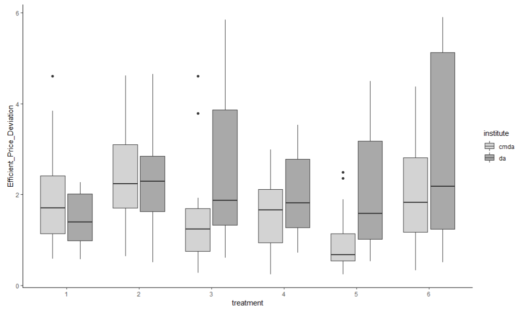


figure 1: Time series examples.

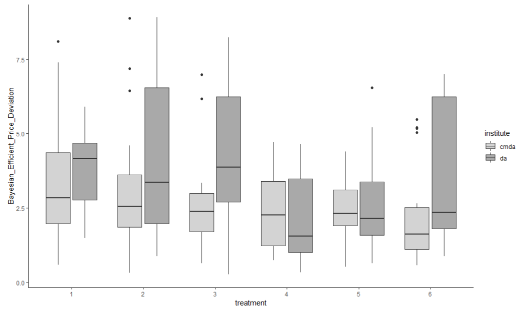
As it can be seen , price rarely converge toward the dividend and in some cases they move around the opening price.

4.1 Market Efficiency and Price Convergence

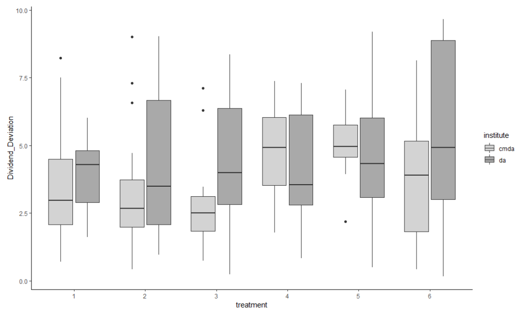
We performs several analysis to test the key aspects of financial markets. In particular, we focus on market efficiency, calculated as discussed before. Graphs show that, moving from one institute to the other, there are some significant improvements for higher level of information quality, as confirmed by the Mann Withney U-test conducted at market level.



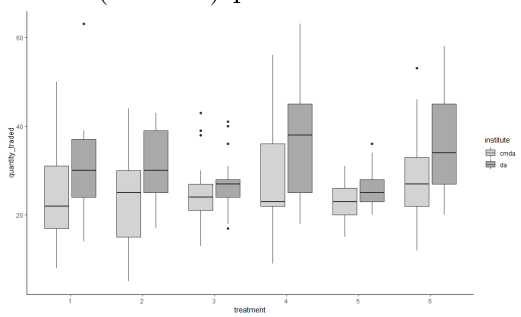
a) Efficient Price deviation (DEP) per treatment.



b) Bayesian Efficient Price deviation ($DBEP$) per treatment.

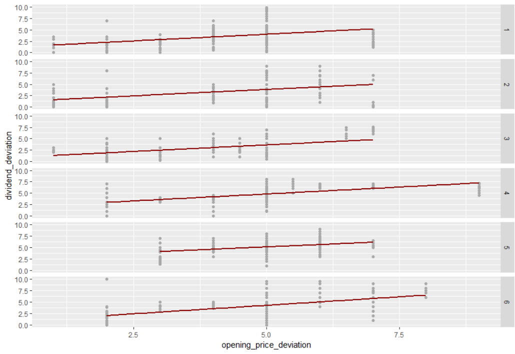


c) Dividend deviation per treatment.



d) Quantity traded per treatment.

As outlined before, the best prediction that a subject can make is the dividend, while it is expected that a subject completely risk-neutral plays close to the average of the information received. As we note from the figures, the deviations from the dividend are smaller in the CMDA institute when the quality of the signal is greater (treatments 1,2,3), however we notice that the prices are closer to the efficiency price in both institutions. Moreover, the quantity traded is systematically lower when a pre-opening phase is introduced, as in Hinterleinter (2016).
A positive linkage between pre-opening price and subsequent prices traded is confirmed by the correlation test between pre-opening and dividend gap from dividend, that is, whenever pre-opening conclude with a misleading price, even in the following trading session those distance persist.



e) Correlation plot.

	Correlation
Treatment 1	0.326 ***
Treatment 2	0.365 ***
Treatment 3	0.534 ***
Treatment 4	0.586 ***
Treatment 5	0.398 ***
Treatment 6	0.485 ***

f) Correlation test.

We formalize this relation by exploiting a random effect tobit model(1) because prices are both lower and upper bounded at 10 and 20 respectively) and a random effect model with robust standard errors(2):

$$P = \alpha + \beta \times OP \times Treatment \tag{1}$$

$$DD = \alpha + \beta \times DOP \times Treatment \tag{2}$$

Where j, t and p are respectively the market id, the exchange sequence number and the correspondent period, P ans OP are $J \times (T \times P)$ matrices, α is a 1×6 vector containing treatments intercepts, β is again a 1×6 vector containing Opening price effects per treatment. We employ data deviation from the dividend with the same notation the random effect model. DD and DOP can be seen as the matrix differences between P and D and OP and D, where D defines a $J \times (T \times P)$ matrix with dividend values. [4]

[4] To avoid cumbersomeness, we pick the best guess a subject can make to model the regression and we do not report random effect model based on the distances between price traded and opening price from others market benchmark because of their linear dependence.

	Dependent variable:	
	price traded	price traded
	censored regression	*panel linear*
	(1)	(2)
opening price	0.719***	0.422***
	(0.105)	(0.076)
treatment 2: opening price	1.140***	0.194**
	(0.180)	(0.092)
treatment 3: opening price	0.283***	0.181**
	(0.106)	(0.092)
treatment 4: opening price	−0.358***	0.207**
	(0.107)	(0.089)
treatment 5: opening price	−0.297***	0.080
	(0.113)	(0.116)
treatment 6: opening price	−0.235	0.463***
	(1.735)	(0.093)
σ_μ	−0.508***	
	(0.126)	
σ_ν	0.565***	
	(0.002)	
constant	yes	yes
Observations	3,209	3,209
R^2		0.203
Adjusted R^2		0.200
Log Likelihood	−6,424.386	
Akaike Inf. Crit.	12,876.770	
Bayesian Inf. Crit.	12,961.800	
F Statistic		73.935*** (df = 11; 3197)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 2: In the mixed effect model, data are expressed in terms of deviation from the dividend.

Intuitively, in each trading session it is expected that each subject correctly react to the arrival of other private signal after some exchanges and the presence of uniformed trader will only slow down the process, maybe it might happen that people infer from incorrect signal, leading to a negative herding behaviour and an high number of losses.
This is why we conduct Philipp-Perron test to account for price convergence, even if this aspect have been rarely attained in literature. It is calculated as:

$$\Delta dd_{jt} = (\rho - 1)dd_{jt} + \upsilon_{jt}$$

and it corrects both autocorrelation and heteroscedasticity. As null hypothesis, ρ is equal to one, i.e. a unit root process is observed and price variation only depends on random error variations[5].

	PP test # of unit root (%)		MW test # null hp acceptance (%)		MW test dividend gap	MW test quantity traded
	DA	CMDA	DA	CMDA	p-value	p-value
Treatment 1	1	0.857	0.809	0.856	0.027	0.04
Treatment 2	0.809	0.952	0.856	0.905	0.068	0.017
Treatment 3	0.952	0.856	0.952	0.856	0.003	0.206
Treatment 4	1	0.952	0.856	0.809	0.876	0.03
Treatment 5	0.952	1	0.809	1	0.68	0.01
Treatment 6	0.952	0.952	0.761	0.905	0.07	0.006

Table 3: Summary table. Phillip Perron test refers to the number of time unit root hypothesis can be not rejected at 5 % significance level , while the Mann Whitney U test columns report the number of times agents play closer to the efficient price with respect the dividend drawn. The last two MW test shows p-values regarding the figures above, testing the alternative hypothesis that dividend gap distribution and quantity traded are lower in the CMDA treatment.

[5]Test has been run on the time series predicted by means of *auto.arima* in R

As predicted, a widespread unit root trend is observed and the consideration made before are supported by the mann-withney wilcoxon runk sum test that lead us to accept a downward location shift of CMDA dividend deviation distribution with respect to DA one, even if price traded are closer to the efficient price in both the institute.

4.2 Fat Tails Returns

It is well known that the distribution of returns belongs to the class of 'fat tail' distributions (Bouchaud 2001). These distributions exhibit a hyperbolic decline of probability mass.
The Hill estimator calculates the tail index, giving us information about the 'fatness' of the tails of the distributions. It considers the log average descending rate of tail values and can be computed as follow:

$$\frac{m}{\sum_i^m (\log x_{n-1+1} - \log x_{n-m})}$$

Where m is the number of observation in the tail and $\sum_i^m (\log x_{n-1+1} - \log_{n-m})/m$ can be seen as the average descending rate from the threshold value. Hence, it can be stated that the flatter is the slope (i.e. the lower will be the differences among the subsequent value from the threshold) the fatter will be the tail.
Empirical studies show that the Hill estimators usually lie in the range [2.5, 5]. Examples include Koedijk et al. (1990), Jansen and de Vries (1991), Loretan and Phillips (1994), Longin (1996), Lux (2002) and Lux and Ausloos (2002). Excess of Kurtosis is another relevants issue that highlights the stationary pattern of the returns distribution (see Morone, 2008), implying that the experimental financial market exhibits more probability mass in the tails and in the centre compared with a normal distribution.

	Kurtosis		Skewness		Hill's Index 95 %	
Treatment	CMDA	DA	CMDA	DA	CMDA	DA
1	10.487 (1.117)	13.090 (2.142)	-0.537 (0.517)	-1.483 (0.477)	1.881 (0.376)	2.202 (0.382)
2	18.783 (4.302)	14.032 (2.165)	-1.817 (0.802)	-0.496 (0.723)	2.081 (0.472)	1.795 (0.286)
3	8.835 (1.101)	10.667 (1.944)	-0.598 (0.415)	-1.119 (0.473)	2.659 (0.571)	3.225 (0.654)
4	13.827 (2.429)	6.701 (0.898)	-1.152 (0.580)	-0.705 (0.231)	2.033 (0.423)	4.049 (1.421)
5	7.084 (1.033)	8.561 (1.445)	-0.999 (0.280)	-0.891 (0.389)	3.807 (0.712)	3.013 (0.534)
6	19.952 (5.635)	17.617 (3.227)	-1.847 (0.623)	-1.847 (0.623)	3.125 (0.631)	2.723 (0.461)

Table 4: Simulated distribution of Kurtosis, Skewness and Hill's index at 5 % level.

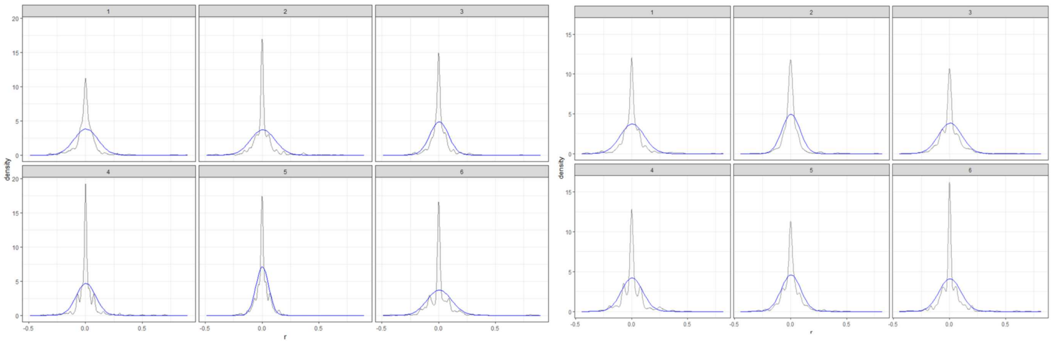


figure 2 CMDA (left) and DA (right) returns distribution.

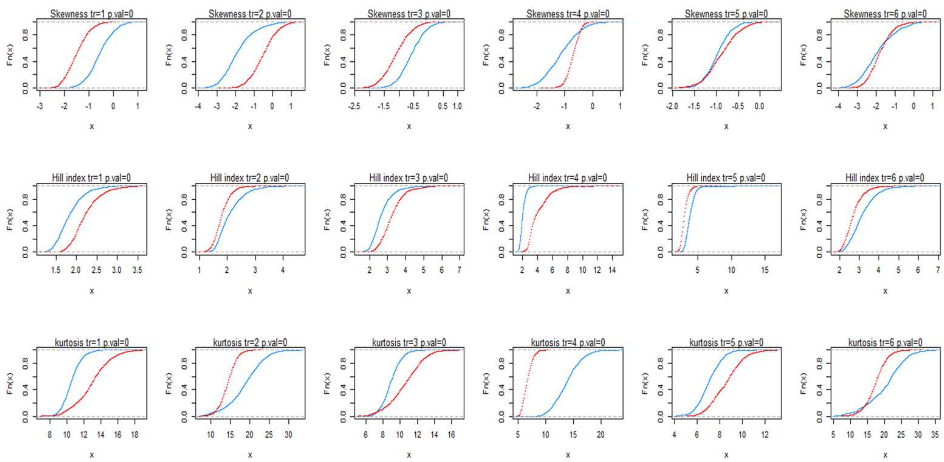


figure 3 Kolmogorov Smirnov test results.

In order to strenghten our result, we make some inference by simulating the distribution of Kurtosis, Skewness and Hill index calculated at 5% level (right tail). Davidson (2009) suggests a computer intensive method, such as bootstrap or other simulation or resampling method and the inclusion of a statistical test to draw conclusion from index that do not have a variance [6]. We iterate the bootstrap 1000 times with the following results (Table 4). Generally speaking, our result are in line with previous one, where distributions are leptokurtic and not fat-tailed (on average, tails lies on the [2.5,5] interval). We run a Kolmogorov-test finding that all the differences among CMDA (blue) and DA (red) are statistical significant, even if there is no mechanism that systematically outperforms each other.

5 Conclusions

In this paper we have discussed the introduction of a pre-opening call market in a countinous double auction trading system. The underlying idea was that this phase might help agents to ameliorate their prior belief at the opening

[6] In his paper he proposes that method to inference on the Gini index. See R. Davidson, "Reliable inference for the Gini Index" (2009) for more details.

of the trading session, leading to a reduction of the most analyized market inefficiencies. The results can be summarized as follow:

- The introduction of a pre-opening phase in itself is not sufficient to improve informational efficiency at the opening of the continuous double auction, even if there is a positive correlation between pre-opening and trading price which suggest that such type of information is not neutral and traders include it in their predictions;
- No convergence is observed in both the institutes;
- Moreover, this hybrid form of market does not reduce the probability to have extra profit, even if it mantains all the aspects of the standalone double auction of our analysis (kurtosis and no-heavy tail).

To conclude, we consider the introduction of a pre-opening phase as a noteworthy tool to inject additional information into the market, maybe it has to be evaluated according the quality degree of the information. Indeed we found that such mechanism in itself it is not sufficient to get model convergence and to lower price efficiencies during trading sessions, conversely it is able to reduce fluctuation and quantity traded and it seems to be more taken into account in accordance with a more precise signal. Further studies might be addressed toward this direction.

Appendix

Here we display the results of the Wilcoxon Mann Withney test. In table 5 we report the pairwise differences between the Bayesian Efficient Market prediction ($DBEF$), the true value of the dividend (DD) and the Efficient Price (DEF) deviation at a market level, while in figure 4 we fully represent market time series. We conduct Mann-Withney test on the basis of the consideration made by observing the boxplot,that is, we test whether Efficient price deviation are effectively smaller than Bayesian Efficient Price and Dividend Price deviation. Moreover, we compare Dividend and BEF deviation even if they are very close to each other.

	DEF/DD	$DEF/BDEF$	$DD/BDEF$
1	0.015	0.006	0.000
2	0.227	0.141	0.000
3	0.000	0.000	0.000
4	0.024	0.000	0.000
5	0.000	0.000	0.000
6	0.480	0.006	0.000

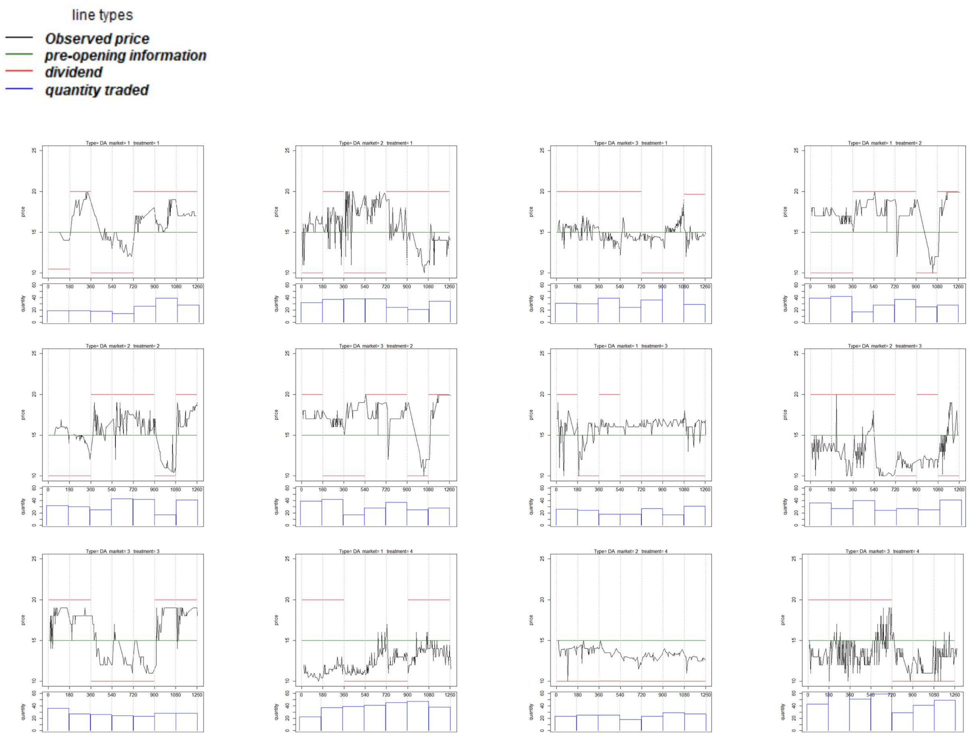
Table 5: CMDA within comparison. Alternative="less"

	DEF/DD	$DEF/BDEF$	$DD/BDEF$
1	0.000	0.000	0.283
2	0.013	0.008	0.325
3	0.002	0.001	0.354
4	0.578	0.000	0.002
5	0.105	0.000	0.006
6	0.205	0.014	0.020

Table 6: DA within comparison. Alternative="less"

	DEF	$BDEF$	DD
1	0.956	0.048	0.048
2	0.599	0.118	0.118
3	0.003	0.001	0.001
4	0.100	0.699	0.834
5	0.001	0.725	0.894
6	0.1303	0.039	0.066

Table 7: Between comparison. Alternative="less",that is, CMDA deviations are lower than DA ones.



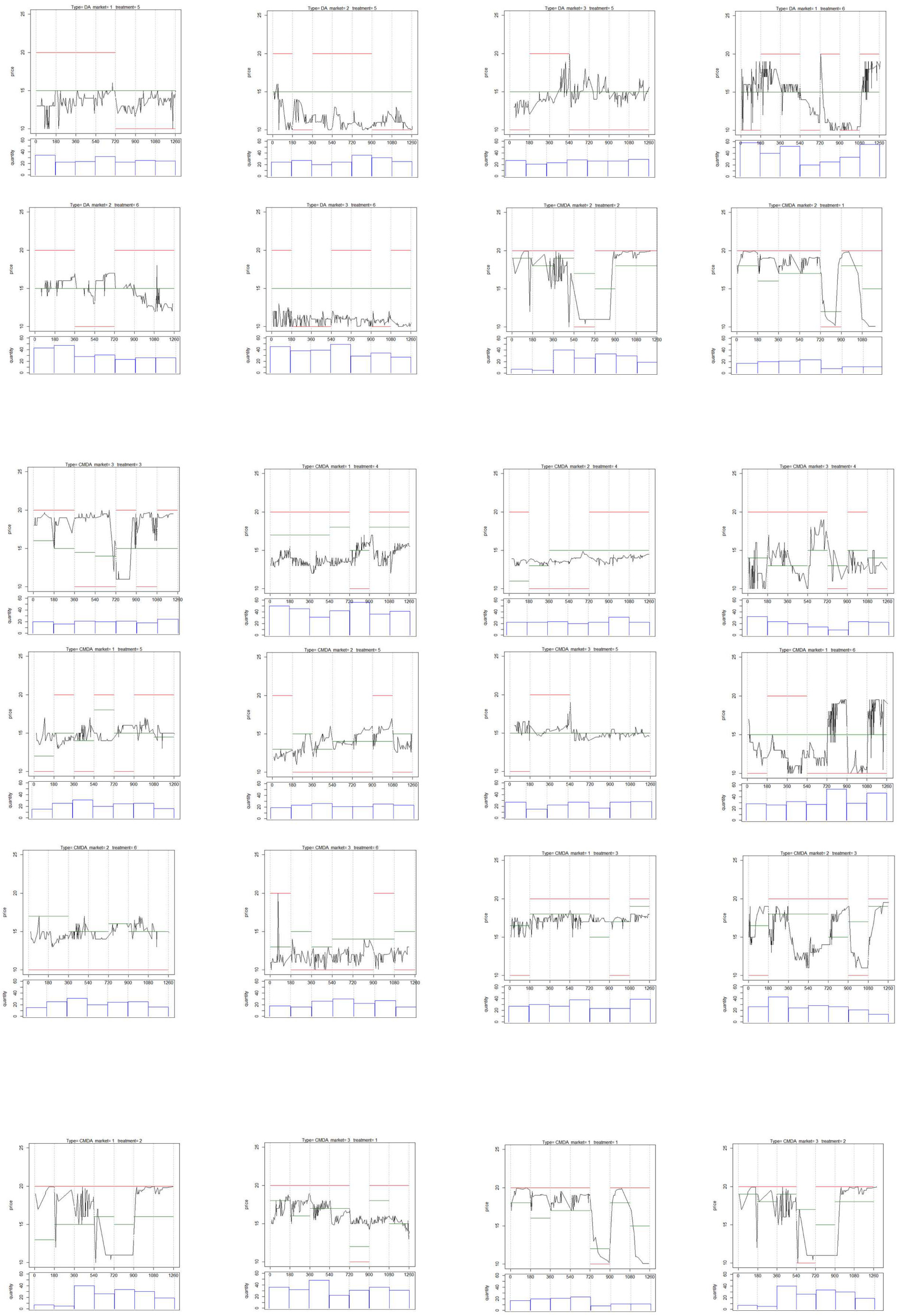


figure 4 full time series representation

References

[1] Banerjee, Abhijit V. , *A simple model of herd behavior* The Quarterly Journal of Economics, 107(3), 797-817,1992;

[2] Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch (1992), *A theory of fads, fashion, custom, and cultural change as informational cascades.* Journal of political Economy,100(5), 992-1026.

[3] Camerer, Colin, and Keith Weigelt (1991), *Information mirages in experimental asset markets*, The Journal of Business, 64(4), 463-493.

[4] Cason, T.N., Friedman, D., 1996., *Price formation in double auction markets.* J. Econom. Dynam. Control 20 (8), 1307–1337.

[5] Fama, Eugene F. (1965), *The behavior of stock-market prices.* The Journal of business, 38(1), 34-105.

[6] Hey, John D. and Andrea Morone (2004) ,*Do markets drive out lemmings—or vice versa?. Economica 71(284),* 637-659.

[7] Hinterleitner, Gernot, U. Leopold-Wildburger, Roland Mestel, and Stefan Palan (2015), *A Good Beginning Makes a Good Market: The Effect of Different Market Opening Structures on Market Quality.* The Scientific World Journal, vol. 2015, Article ID 307808.

[8] Hornung, Philipp Leopold-Wildburger, Ulrike Mestel, Roland Palan, Stefan. (2014), *Insiders' behavior under different market structures. Experimental evidence on trading patterns, manipulation and profitability.* Central European Journal of Operations Research. 23. 10.1007/s10100-014-0359-2.

[9] Madhavan, *Trading mechanisms in securities markets.* Journal of Finance, vol. 47, no. 2, pp. 607–641, 1992.

[10] Noussair, Charles, and Yilong Xu (2015) *Information mirages and financial contagion in an asset market experiment.* Journal of Economic Studies, 42(6), 1029-1055.

[11] Nuzzo, Simone and Andrea Morone (2017), *Asset markets in the lab: A literature review.* Journal of Behavioral and Experimental Finance, http://dx.doi.org/10.1016/j.jbef.2017.02.

[12] Oksana Doherty (2018), *Informational cascades in financial markets: review and synthesis*, Review of Behavioral Finance, Vol. 10 Issue: 1, pp.53-69, https://doi.org/10.1108/RBF-05-2016-0030.

[13] Ozlem Akin José M. Marín José-Luis Peydró, (2016), *Anticipating the financial crisis: Evidence from insider trading in banks*, Economics Working Papers 1524, Department of Economics and Business, Universitat Pompeu Fabra.

[14] Plott, Ch., Sunder, S., 1982. *Efficiency of experimental security markets with insider information: an application of rational expectations models.* Journal of Political Economy 90, 663-698.

[15] Schnitzlein, C.R. (1996) *Call and continuous trading mechanisms under asymmetric information: an experimental investigation.* Journal of Finance 51(2), 613-636.

[16] Theissen, Erick. (2000) *Market structure, informational efficiency and liquidity. An experimental comparison of auction and dealer markets*, Journal of Financial Markets 3(4), 333–363.