

Microstructure, incentives, and the discovery of equilibrium in experimental financial markets

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ABSTRACT

We analyze the discovery of (or deviation from) equilibrium strategies and valuations in experimental financial markets with differential information, in the spirit of Plott and Sunder (1988). We consider three different market microstructures: i) a continuous oral double auction market, ii) a call market followed by a continuous market, and iii) a preopening period followed by a call market and then a continuous market. We characterize theoretically equilibrium strategies in this trading game. Our experimental results are consistent with tâtonnement during the preopening period facilitating the discovery of the equilibrium strategies and prices in the opening call auction. We also find that incentivizing subjects in the experiments is necessary for convergence and learning.

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1 Introduction

Do economic agents play according to the implications of game theory ? What are the consequences of the organization of the market for the discovery of (or deviations from) equilibrium strategies and prices ? Is private information revealed in the market process ? Experiments offer a useful methodology to examine these issues. They enable the researchers to observe all the actions and information sets of the agents, and to design situations where equilibrium outcomes and deviations from equilibrium can be clearly identified. Varying the experimental design, one can obtain insights as to which situations are more or less conducive to learning.¹

We investigate these questions in the context of financial markets. We study how the microstructure of the market influences the process through which agents discover asset valuations and equilibrium strategies. To study these points, we rely on the Plott and Sunder (1988) asymmetric information experimental asset market. While their seminal analysis was set against the theoretical benchmark of competitive rational expectations equilibria, we take a game theoretic approach, emphasizing the strategic nature of the interaction between the participants of the trading game and focusing on their equilibrium strategies.

In equilibrium in our trading game, prices and order flow reveal information about asset values. In the Arbitrage Free Perfect Bayesian Equilibria,

¹This is in the spirit of Plott and Smith (1978), who compare the efficiency of two different market structures (a continuous auction and a fixed posted price auction) and Bronfman et al. (1996) who compare double oral auctions and Walrasian tâtonnement. Differences between these papers and ours include the following: i) while they consider private values context, we focus on a common value situation, where, during the trading process, subjects must learn the information content of the actions of the others, ii) the market structures we consider are different from those analyzed in Plott and Smith (1978) and Bronfman et al. (1996).

there are no trades, except at fully revealing prices. This implies that in equilibrium agents cannot incur losses. Consequently, we identify trading losses and unprofitable orders observed in the lab as deviations from equilibrium. These deviations can be interpreted as a noise trading component in the order flow. To the extent that they are observed in the experiment, these deviations provide a behavioral foundation to the noise trading component of the order flow often assumed in market microstructure models (see e.g. Glosten and Milgrom (1985) or Kyle (1985)). One feature they have in common is that they lead to systematic losses.

To analyze if price discovery and convergence to equilibrium vary across different market microstructures, we compare 3 different market designs, corresponding to existing markets. First we consider a continuous oral double auction, as in Plott and Sunder (1988). Second we consider a call auction followed by a continuous trading phase. Third we consider a call auction, followed by a continuous trading phase, and preceded by a preopening period, during which traders can place, revise and cancel orders, and indicative prices are set. These three market structures, whereby traders place limit and market orders, are very similar to those prevailing in practice. One difference, however, is that these markets are fully electronic, while our subjects are physically present in the classroom and verbally announce their orders. While on Nasdaq there is essentially only a continuous market (as in our first market structure), on the London Stock Exchange on the SETS system orders are crossed at a uniform price before the continuous market (as in our second market structure), and in the Paris Bourse, the electronic German market (Xetra), the Madrid Bolsa, the Borsa Italiana, and the Bovespa in Brazil, there is a preopening period before the opening call auction (as in our third market structure).² Comparing, in a controlled experimental set-up, the different market microstructures existing in the real world, enables one to shed some light on their relative performance in terms of price discovery and learning. The theoretical restrictions on equilibrium actions that we derive apply to the three market structures. This enables us to use the same theoretical benchmark to interpret deviations from equilibrium in the three market structures. We can thus analyze how the microstructure of the market affects price discovery and convergence towards equilibrium in a context where it does not affect equilibrium. This is a first step towards

²On the other hand, the market structure of our trading game differs markedly from that prevailing on the New York Stock Exchange, because we do not have a specialist. There is also a difference between our market game and NASDAQ because we do not have designated dealers.

studying which trading mechanisms are the most conducive to learning of equilibrium.

We ran the experiment with 25 different cohorts of students from Toulouse University. 9 out of these 25 cohorts faced strong explicit incentives to maximize profits, as these directly affected their course grade. The other 16 cohorts faced less strong and explicit incentives. 25 is a rather unusually large number of cohorts. This wealth of data enables us to conduct statistical tests across cohorts, which constitute arguably quite independent observations.

We find that explicit and strong incentives are necessary for subjects to learn to play equilibrium strategies and for price discovery to be efficiently achieved. This is in line with Camerer and Hogarth (1999) who find that incentives are key to inducing subjects to exert effort, to make smart judgments and decisions.

We also find that, when there is a preopening period, deviations from equilibrium strategies are less frequent, and price discovery is more effective. This could stem from subjects using the initial preopening “tâtonnement” round to conduct inferences and initiate learning.³ Indeed, we find that pricing errors during the preopening phase tend to be corrected in the opening call auction.

In the line of Camerer (1999), one interpretation of our findings about the preopening period is that it modifies the mental representation of the game. By enabling the subjects to play a warming round, it makes it less difficult for subjects to accurately evaluate the consequences of their actions and understand their interactions with the others. In some sense, the preopening reduces the cost of thinking efficiently about trading strategies. In fact, we find that even when the subjects do not face strong incentives, the preopening period reduces the frequency of unprofitable deviations from equilibrium.

To compare our experimental data to field data, we use the opening and preopening prices generated in our experiments to run unbiasedness regressions similar to those estimated by Biais, Hillion and Spatt (1999) based on field data from the Paris Bourse. Similarly to the results obtained with field data, we find that the hypothesis that opening prices are conditional expectations of the value of the asset cannot be rejected.

Our paper is related to the analysis of price discovery and the conditions under which experimental markets converge towards equilibrium by Plott

³On tâtonnement process in experiments see Bronfman et al (1996).

and Sunder (1982), Forsythe, Palfrey and Plott (1982), Plott and Sunder (1988), Forsythe and Lundholm (1990), Schnitzlein (1996) and Krahen and Weber (1999). Our results complement theirs in the following ways:

- We characterize theoretically the equilibrium strategies of the agents in the trading game, and study deviations from or convergence to these equilibrium actions. This leads us to focus on the orders placed in the game, rather than only on the prices set in the experimental market.
- We compare three different market structures: the continuous market, the call market and the preopening period.
- We study the role of the incentives faced by the subjects.

Our focus on strategies is in the line of the experimental analyses of auctions by Kagel and Levin (1986), and bargaining games by Roth, Prasnikar, Okuno-Fujiwara and Zamir (1991). It is less frequent in the analysis of experimental financial markets.⁴ This may reflect that strategies in experimental financial markets are rich and complex. For example they are often dynamic and can involve manipulation, so that identifying equilibrium benchmarks is problematic. In the present paper we bypass this difficulty, by offering a simple way to differentiate between actions which are consistent with equilibrium and actions which are not.

The next section presents the trading game and equilibrium strategies. Section 3 presents the experimental design. Our results on order placement strategies are in Section 4, while Section 5 presents results on price discovery. Section 6 concludes. The proof of Proposition 2 as well as a sample of the instruction sheet given to the subjects in the experiment are in the appendix.

2 Trading game and equilibrium strategies

2.1 Trading game

The structure of the asset payoffs, the endowments and the signals are as in Market 7, Series C, in Plott and Sunder (1988). There is a single risky asset, paying at the end of the game a liquidating dividend. The value of

⁴See however Cason and Friedman (1997) who, in the context of a one shot call market, analyze the extent to which subjects in the laboratory follow the equilibrium strategies theoretically derived by Rustichini, Satterthwaite and Williams (1994).

the dividend can be 490 francs, 240 francs or 50 francs with equal probability. Before the start of the game, the players receive heterogeneous private signals. When the dividend is 490 francs, half the players know that it is not 240 francs while the other half know it is not 50 francs. Similarly when the dividend is 240 francs, half the players know it is not 490 francs, while half the players know it is not 50 francs, and when the dividend is 50 francs, half the players know it is not 490 francs, while half the players know it is not 240 francs. Each agent starts each replication of the game with 4 shares and 25000 francs. Unlike in Plott and Sunder (1988) short sales are allowed. As in financial markets in the field, players can place limit orders and market orders. Limit sell orders specify the number of shares the agent offers to sell, as well as the minimum price below which he is not willing to sell. Limit buy orders specify the number of shares the agent offers to buy, as well as the maximum price above which he is not willing to buy. To express his willingness to trade against a limit order to buy (resp. sell) at price p an agent can place a limit order to sell (resp. buy) at a lower (resp. higher) price. Equivalently the player can place a market order.

In our theoretical analysis we assume the structure of the game is common knowledge, and, in the experiment, we endeavour to ensure that this assumption holds (see next section).

2.2 Theoretical analysis

If the agents have the same utility function, the initial allocation is Pareto optimal, hence the no trade theorem (Aumann (1976), Milgrom and Stokey (1982)) applies, and the following proposition obtains.

Proposition 1

In equilibrium, when agents have the same utility function and common priors there are no trades, except at fully revealing prices.

In contrast, if agents have different utility functions, the initial allocation is generally not Pareto optimal. Yet there exist equilibria whereby no trade takes place, except possibly at the fully revealing price. This is stated in the following proposition.

Proposition 2

Even if agents have different utility functions, there exists a class of equilibria with no trades except at fully revealing prices. The corresponding equilibrium strategies are the following: Agent i , on receiving the signal “not 490”, offers to sell at price $p_i \geq 240$. Agent j , on receiving the signal “not

50", offers to buy at a price $p_j \leq 240$. Agents receiving the signal "not 240" refuse to trade.

In this equilibrium, if the dividend is 50, agents having observed "not 490" offer to sell at prices larger than or equal to 240, while agents having observed "not 240" refuse to trade. Consequently there is no trade in equilibrium in this state of the world. If the dividend is 240, agents having observed "not 490" offer to sell at prices larger than or equal to 240, while agents having observed "not 50" offer to buy at prices lower than or equal to 240. Consequently there is either no trade, or trading at the fully revealing price: 240. The situation arising when the dividend is 490 is symmetric to the situation arising when the dividend is 50. Note that, by observing the equilibrium actions, an outsider can infer exactly what the value of the dividend is, i.e., equilibrium is fully revealing.

Proposition 2 describes a *class* of equilibria, to the extent that agents having observed "not 490" (resp. "not 50") select between a continuum of equilibrium actions, namely the prices in the interval $[240, 490]$ (resp. $[50, 240]$). Note however that utilities and allocations are the same irrespective of which prices are picked in these intervals.

In addition to being Perfect Bayesian equilibrium strategies, the orders described in Proposition 2 are ways in which the agents can *attempt* to seize arbitrage opportunities. For example, selling at a price not lower than 240 when the value of the asset cannot be higher than 240 constitutes an arbitrage opportunity. Yet, in the equilibrium characterized in Proposition 2, there are in fact no arbitrage opportunities.

In the trading game we analyze there might exist other equilibria than the no trade equilibrium characterized in Propositions 1 and 2. Equilibrium trading could arise between two agents, with the same signal, engaging in risk sharing trades. For example, consider two agents having observed "not 490" and suppose one is risk neutral and the other very risk averse. In this context, if the risk neutral agent bought shares from the risk averse agent at a price slightly below $\frac{50+240}{2} = 145$ welfare would be enhanced. Yet, if the risk-averse agents with signals equal to "not 490" attempted to engage in such sales, then agents with signal equal to "not 50" would find it attractive to buy at this price. Since signals are private information, risk-averse sellers could not tell such arbitrageurs apart from risk neutral agents with signal equal to "not 490". Thus trading strategies attempting to share risk would generate arbitrage opportunities. Hence we can state the following corollary.

Corollary 1

Absence of arbitrage opportunities implies that in equilibrium there are no trades except possibly at fully revealing prices.

Since, in the context of financial markets, it is natural to impose the restriction that there should not be arbitrage opportunities, we will focus, hereafter, on the Arbitrage Free Perfect Bayesian Equilibria, i.e., the equilibria characterized in Propositions 1 and 2. In this context, trades generating losses cannot occur, since there is either no trade or trades at fully revealing prices. Neither can there be any offer which would have led to losses. This is stated in the following corollary:

Corollary 2

In the Arbitrage Free Perfect Bayesian Equilibria of the trading game, there are no trades generating losses, and no order which would result in a trading loss if it was executed.

When analyzing the data generated in the experiments, we will rely on the above corollary to identify deviations from equilibrium, corresponding to trading losses or to orders potentially generating trading losses.⁵

Note that analyzing orders (in addition to transaction prices as in Plott and Sunder 1988) is informative because it entails studying directly the strategies of the agents, and correspondingly the deviations from and convergence to equilibrium strategies. Also, empirical research in market microstructure has provided ample evidence that the order flow contains significant information. Trading losses represent an additional interesting source of information relative to deviations from and convergence to equilibrium.

So far, we have not described or relied upon the extensive form of the trading game. In fact the equilibria presented above, and their consequences stated in the corollary hold independently of this extensive form. In the case where the agents have identical preferences and the no-trade theorem applies this is straightforward. In the case where the agents can have different preferences, this hinges on the structure of the out-of-equilibrium beliefs, which precludes dynamic manipulations strategies whereby agents would buy to drive up prices and then sell at inflated prices.

Since the restrictions imposed by equilibrium are independent of the extensive form of the trading game, i.e., the microstructure of the market, we can rely on the same theoretical benchmark when analyzing the actions

⁵Note however that the best response to out of equilibrium actions may not be to play equilibrium strategies.

taken in the experiments in the three different market structures. Hence we analyze how the microstructure of the market affects deviations from and convergence towards the equilibrium.

3 Experimental design

We ran the experiment with 25 different cohorts of students from Toulouse University. Subjects were undergraduate and graduate students in economics and management without previous exposure to experiments or market microstructure. The experiment was run in the context of courses taught on stock markets. Each cohort included between 8 and 13 subjects. Each cohort participated to 3 to 5 replications of the experiment, and this within a single market structure. We randomly drew the realizations of the final value of the asset.

3.1 Market structure

We analyzed three types of market.

We studied a continuous oral double-auction structure identical to the setting in Plott and Sunder (1988, market 7, series C). Each continuous double-auction lasts seven minutes. During this period, the subjects can place limit orders for one share each in continuous time, by announcing them verbally to the experimentator. The experimentator writes these offers on the board. The other players see and hear the occurrence of these orders. They can hit these orders by placing market orders or marketable limit orders. Whenever this is the case transactions take place, and this is observed by the other players. As long as their orders have not been hit, subjects can cancel them.

We also considered a variant of this market structure where i) the opening price and trades are determined through a uniform-price batch auction (a call) and ii) this is followed by a continuous double-auction, operating as described above. In the opening call auction, traders can post limit orders. These orders are transmitted to the experimentator as sealed bids and offers for up to ten shares at each price, written on a piece of paper. Using these orders the experimentator constructs an aggregate supply and an aggregate demand curve, and sets the opening price at the level maximizing trading volume. This price is announced publicly to the subjects. In addition the subjects receive written confirmations of the execution of their orders at the uniform opening price.

Furthermore, we considered another variant with a preopening period prior to the opening call auction and the following continuous trading phase. The opening call auction and the following continuous trading phase operate as described above. The workings of the preopening period are as follows. As in the opening call, agents place sealed bids and offers—limit orders which are aggregated by the experimentator to determine the uniform volume maximizing price. This price is publicly announced to the traders. No trades occur at this preopening price, however.

3.2 Subjects and incentives

The rules of the game were presented to the subjects in a 90 or 120 minutes class before the experiment. During this class the subjects asked questions and clarifications about the rules of the game. The experimentator endeavored to answer all clarifying questions while refusing to discuss questions such as : How should I play ? What should I do in this circumstance ? Is this a good strategy ? etc... We explained to the students that we did not answer these questions in order not to influence their behavior during the auction, we also announced them that, after the experiments we would have a debriefing session where we would analyze the game together. At the beginning of the experiment, each cohort received a written document stating the rules of the game (an example is displayed in Appendix 2). The experimentator reexplained the game to the subjects, and they asked additional clarification questions. The subjects were also handed forms to write down the orders they placed during the preopening period or the opening call, and to record their trades, cash balances and inventories during the continuous market.

The subjects were instructed to maximize their final wealth. At the end of each replication of the game the experimentator asked verbally to the subjects what they thought the value of the dividend was (490, 240 or 50). Then the experimentator announced what was actually the realized value. Subjects then computed their final wealth. The experimentator checked these computations and then announced publicly and nominally the wealth of each of the subjects, complimenting those who had done well and gently teasing those who had done poorly.

9 cohorts of students were also announced verbally and in the written document that their grade for this course would reflect the final wealth they obtained in the replications. The grade for the course is between 0 and 20. There is a final exam, for which grades are typically between 6 and 14.

Students participating to 4 replications of the game earned bonus points (to be added to their final exam grade to determine the course grade) equal to:

$$\frac{\sum_{I=1,\dots,4}(W_i - 23000)}{3000}.$$

Students participating to 3 or 5 replications earned bonus points computed according to a similar formula designed to avoid biases in grading reflecting differences in numbers of replications. We believe that rewarding subjects based on exam grades, as opposed to relatively small amounts of money is likely to induce serious, earnestly optimizing behavior, and to deter gambling.⁶ In practice, subjects earned between 0 and 7 points in the game, with an average close to 4. To avoid influencing the students into trades that they did not feel beneficial, we repeatedly announced them during the experiments that they did not have to place orders and that their only concern should be to maximize their bonus.

Table 1 shows the number of cohorts which participated in the different market structures and whether they faced strong explicit incentives or not. In the analysis below we analyze how differences in market structures and in incentive schemes affect convergence to equilibrium strategies and price discovery. These analyses are based on the 25 cohorts which participated to the experiment. This is a rather unusually large number of cohorts relative to other studies in experimental economics. This wealth of data enables us to conduct statistical tests across cohorts, which constitute arguably quite independent observations.

3.3 An example

To provide some feeling for our experimental data, Figure 1 plots the pre-opening and opening supply and demand, as well as the dynamics of the best bid, the best ask and the transactions prices during the continuous trading phase, for 2 replications, for the same cohort, which faced strong and explicit incentives.

Preopening and opening supply, demand and prices as well as the dynamics of prices and offers in the continuous market during the first replication of the game are plotted in Figure 1, Panels A, B and C. The preopening price was 270, somewhat above the value of the asset, 240. The opening

⁶Note also that, from the pedagogic point of view, given that one of the most fundamental economic messages we want to convey to students in economics is profit maximization, this grading scheme seems appropriate.

price was lower (260) consistent with the market initiating learning. Yet the market failed to learn the equilibrium valuation of the asset. While numerous limit sell orders were placed at prices above 240, consistently with the equilibrium characterized in Proposition 2, these offers were frequently hit by market buy orders. These market orders incurred losses, and were inconsistent with equilibrium.

It turns out that, for the same cohort, at the third replication of the game, the value of the asset was 240 again. Panels D, E and F in Figure 1 illustrate graphically the supply and demand curves during the preopening and opening as well as the dynamics of prices and offers in the continuous market during the third replication of the game for this cohort. The pre-opening price was equal to the value of the asset, 240, as well as the opening price. Convergence to equilibrium during the continuous trading phase was almost immediate and quasi perfect, as the subjects placed limit orders to sell at or above 240 and limit orders to buy at or below 240, while nearly all market orders were executed at 240.

4 Do orders reflect learning of the equilibrium strategies ?

4.1 Weak rationality

Maybe the weakest possible restriction imposed by rationality is that agents should not submit orders which, given their own information, are *bound* to generate losses. Such irrational orders would arise if an agent sold or offered to sell at a price lower than 240 after observing the signal “not 50”, or if he bought or offered to buy at a price above 240, after observing the signal “not 490”. Across the 9 cohorts with strong and explicit incentives the average proportion of the orders which reflected such irrational behavior was 3%. Across the 16 cohorts which did not face strong explicit incentives the proportion of orders bound to generate losses given the private signal of the trader was equal to 7 % (the t-statistic for the difference between these two averages is 1.89). Note however that, as illustrated in Figure 2, the difference between cohorts facing strong incentives and the others is apparent only for the first replication of the game. This suggests that subjects quickly learn not to place orders inconsistent with their private signals, irrespective of the incentive scheme they face.

4.2 Strong rationality

A stronger restriction imposed by rationality would be that agents play strategies consistent with the Arbitrage Free Perfect Bayesian Equilibrium characterized in Proposition 2. To investigate if this restriction is violated we rely on the criterion spelled out in Corollary 2: orders that would lead to losses if they were executed are inconsistent with the Arbitrage Free Perfect Bayesian Equilibrium. (We will hereafter refer to such orders as “inconsistent with equilibrium”).

4.2.1 Empirical analysis

Incentives, market structure and deviations from equilibrium We computed for each cohort the proportion of orders inconsistent with equilibrium averaged across the replications of the game to which the cohort participated. Figure 3 plots the average across cohorts of this measure of deviations from equilibrium, conditional on whether the subjects face strong and explicit incentives or not, and conditional on the market structure. As the figure illustrates, the proportion of orders inconsistent with equilibrium is lower when the subjects face strong and explicit incentives (and this whatever the market structure), and also when the market involves a preopening period (and this whatever the incentive scheme).

To provide more systematic information on these points, we regressed our measure of how much the cohort deviated from equilibrium onto predetermined variables: a constant, a dummy variable taking the value one if the cohort faced strong and explicit incentives, a dummy taking the value one if the cohort played in the market with a call and a continuous trading phase, a dummy taking the value one if the cohort played in the market with a preopening period, and, as a control variable, the proportion of replications of the game for that cohort where the value was 240. The latter variable is introduced to control for the precision of the signals of the agents, as, when the value is 240, all agents have quite precise signals, while, when the value is 490 or 50, half the agents have a more ambiguous signal: “not 240”. To facilitate the interpretations, all the regressors (except the constant) were defined so that they had 0 mean. For example, consider the variable indicating if the cohort faced strong and explicit incentives. It takes the value one when there are such incentives, and the value $\frac{-p_I}{1-p_I}$ otherwise, where p_I is the proportion of cohorts with strong and explicit incentives, namely $\frac{9}{25}$.

The estimates of this regression, ran across the 25 cohorts, are in Table 2.

Note that the adjusted R^2 is rather large, as it is equal to 80%. This suggests that our regressors do a good job at capturing the sources of heterogeneity across cohorts as regards deviations from equilibrium.

First consider the intercept, which is equal to the unconditional mean of the proportion of orders inconsistent with equilibrium in our data. It is equal to 36.25 %, and is statistically significantly different from zero. These deviations between the observed orders and the Arbitrage Free Perfect Bayesian Equilibrium strategies can be interpreted as a noise trading component in the order flow. One feature they have in common with the noise traders commonly assumed in market microstructure models (see e.g. Glosten and Milgrom (1985) and Kyle (1985)) is that they systematically lose money.

One might wonder if the order flow observed in our experiment differs from purely random orders, i.e., are there only noise traders in this experimental market ?⁷ A reasonable description of purely random strategies would be the following: randomly choose to buy, with probability one half, or sell with the complementary probability; randomly choose to place an order at a price above 240, with probability one half, or below 240 with the complementary probability. (Prices above 490 and below 50 are not taken into account). Were the agents to follow such strategies, the proportion of orders inconsistent with equilibrium would be 50%. So to investigate if the order flow in our data significantly differs from pure noise trading, we must test if the observed proportion of orders inconsistent with equilibrium (36.25 %) is significantly below 50%. As the standard error of the estimate of the intercept in our regression is 0.82% this is obviously the case. Hence the pure noise hypothesis is rejected.

Now turn to the indicator variable reflecting the presence of strong and explicit incentives. It is significantly negative. Its value (-10.85%) means that, other things equal, the average proportion of orders inconsistent with equilibrium when the subjects face strong and explicit incentives drops down to 25.65%, which is 10.85 percentage points lower than the unconditional average.

⁷This is related to the analysis of zero-intelligence traders by Gode and Sunder (1993). There are two differences, however. First, while we only rely on experiments, Gode and Sunder (1993) rely on simulations when they analyze how imposing budget constraints drives the market close to equilibrium. Second, in their private value environment loss making trades (and correspondingly budget constraints) are easy to define, while in the present common value environment it takes quite a bit of subtlety for the subjects to find out what trades are loss-making. In fact, finding this out basically amounts to discovering the equilibrium.

While the indicator of the market structure where there is a call and a continuous market phase is negative (which suggests that the presence of a call market helps discover the equilibrium), it is only marginally significant. The coefficient of the indicator of the market where there is a preopening is equal to -8.4% and is significantly negative. This suggests that the preopening phase is important to ensure that the opening call auction operates satisfactorily. Our estimates imply that the average proportion of orders inconsistent with equilibrium when there is a preopening period is 28.1%, which is 8.4 percentage points lower than the unconditional average.

Finally, the coefficient of the proportion of replications where the value is 240 is significantly positive. Somewhat surprisingly, this suggests that subjects are more prone to make mistakes when they have precise signals. This may reflect that subjects with precise signals exhibit overconfidence which makes less aware of the winner's curse risk.

Learning To illustrate the patterns of learning in these markets, Figure 4 shows how the average proportion of orders inconsistent with equilibrium varies as subjects become more experienced. As is illustrated by the figure, while subjects learn equilibrium strategies when they face strong and explicit incentives, especially if there is a preopening, they do not seem to converge towards equilibrium when they do not face strong explicit incentives.

To document this phenomenon more systematically, we computed, for each cohort, the difference between the average proportion of orders inconsistent with equilibrium during the last two replications of the game, and that proportion during the first two replications of the game. Learning of the equilibrium, translating into a decrease in the proportion of orders inconsistent with equilibrium, leads to a negative sign for this variable. To study what factors affect learning, we regressed it onto the same predetermined variables as in Table 2. We also included in the regressors the proportion of orders inconsistent with equilibrium during the first two replications of the game. The idea is to allow for the possibility of error correction phenomena: do the cohorts which deviated a lot from equilibrium realize it, and reduce more strongly during the last two replications of the game the proportion of orders inconsistent with equilibrium? Note further that, again to facilitate the interpretations, all the regressors are defined so that they have 0 cross-sectional mean. In the case of the proportion of orders inconsistent with equilibrium during the first two replications of the game, this simply means that we subtracted the cross-sectional average from the value of the

variable for each of the cohort.

The estimates of this regression, ran across the 25 cohorts, are in Table 3. Note that the adjusted R^2 is somewhat lower than in the previous regression, but still reasonably large, as it is equal to 47%.

First consider the intercept, which is equal to the unconditional average of the change in the proportion of orders inconsistent with equilibrium. It is statistically significantly different from zero, so that the hypothesis that there is no learning is rejected. Its value means that the average proportion of orders inconsistent with equilibrium is on average 3.5 percentage points lower during the last two replications of the game than during the first two.

Now turn to the indicator variable reflecting the presence of strong and explicit incentives. It is significantly negative, so that the hypothesis that incentives do not affect learning is rejected. Its value means that when the subjects face strong and explicit incentives the decrease in the proportion of orders inconsistent with equilibrium is 15.8 percentage points greater than the unconditional average. This suggests that the consequences of incentives for learning are quite important.

The variable taking value one when there is a call opening (but no preopening) is not significantly different from zero, while the indicator of the preopening is only very marginally significant. This suggests that, while the preopening phase reduces the extent to which the subjects deviate from equilibrium, it does not very significantly enhance the speed at which they converge to equilibrium.

Finally note that the proportion of orders inconsistent with equilibrium during the first two replications of the game has a significant impact. This suggests that error correction phenomena are indeed at work in the experiment.

4.2.2 Interpretation

The role of the market structure In equilibrium, the market structure has no consequence on trades and information revelation. Hence it does not matter if there is a preopening period or not. Yet, when equilibrium has not been learned yet, the subjects must figure out the optimal order placement strategies and the information content of trades. In this context, the preopening tâtonnement period seems to help them think through the trading game.

This could be interpreted in terms of mental representations of the game. Kagel, Harstad and Levin (1987) find empirical evidence contradictory with

the theoretical equivalence between English auctions and sealed bid second price auctions. Camerer (1999) interprets the different behaviors observed in the two auctions formats in terms of mental representations. He notes that figuring out the conditions under which a bid wins the auction is easier in the English auction “because the external representation economizes on working memory required to express bidding behavior.”

Similarly, in the present experiment, it is possible that the initial pre-opening tâtonnement modifies the mental representation of the trading game. For example, thinking about their order placement strategies during the initial virtual preopening call could make it easier for the subjects to design their orders in the following opening call auction. Also, observing the outcome of the initial preopening call could help the subjects initiate the thinking process leading to clever order placement during the opening call auction. In the next section we present further evidence consistent with that interpretation.

Learning and price discovery during the preopening could be hindered by manipulative behavior, however. In practice, we noticed very little occurrence of such behavior in the replications of the experiment. Only in one case was it obvious to the experimentator that such manipulation of the preopening price was taking place. Interestingly, the market proved very resilient to this manipulation, which eventually had little impact on the opening price and the continuous market. This replication of the experiment is illustrated in Figure 5, Panels A, B and C, where the value of the asset was 240. One of the subjects had observed the signal “not 50”. To manipulate the market into believing that the value was low, in order to be able to buy at low prices, she submitted large sell orders during the preopening. Consequently the preopening price was set to 100. Now, the other subjects who had observed “not 50” interpreted this low price as the indication that they could buy at advantageous prices at the opening. Consequently they placed large buy orders, which drove the opening price up to 230, fairly close to the true value of the asset.

The role of incentives Our results underscore the crucial role played by incentives. This is in line with the findings of Camerer and Hogarth (1999). They analyze the performance of experimental subjects as the result of the efforts they exert (a form of *labor*) and of their cognitive *capital* (knowledge base and skills). They emphasize that incentives are important to induce the subjects to exert effort. Similarly, in our experimental market, subjects need

to exert efforts to accurately analyze the trading environment, and endeavor to make smart decisions and judgement to earn profits, rather than simply taking fun in the game.

Our findings that little learning occurs without incentives also suggest that there is a limit to the extent to which (cognitive) capital can substitute for labor (effort), as in Jamal and Sunder (1991). While the experience acquired by the subjects in our experimental trading game is a form of cognitive capital, experienced subjects tend to place unprofitable orders only if they face strong incentives. Our experimental results therefore point at the complementarity between experience and the effort induced by appropriate incentives.

Note also that convergence to equilibrium is enhanced by the preopening even when there are no strong incentives. In line with our above remarks about mental representations, our interpretation of this result is the following: When there is a preopening period, it is easier for the subjects to come up with an effective and adequate mental representation of the consequences of their actions. Hence, the level of effort needed to make accurate and performing judgements and decisions is lower. Consequently incentives are less necessary. This suggests that structures facilitating mental representations (such as the preopening), can to some extent substitute for incentives to generate performance in experiments.

5 Price discovery

5.1 Mean absolute deviation between the true value of the asset and opening call prices or continuous market prices

To provide a quantitative assessment of the extent to which pricing in the experimental market converged to the true value of the asset, we computed, for each cohort and replication of the game, the mean absolute deviation (MAD) between the true value of the asset and the transaction prices. The average across cohorts of the MAD is plotted in Figure 6, for each of the replications of the game. Panel A presents the results when focusing on call opening prices only while Panel B presents the results based on transaction prices established in the continuous trading phase of the market (since not all cohorts participated in call opening auctions Panel A is based on less many observations than Panel B).

Figure 6 illustrates the striking difference between the cohorts which faced strong explicit incentives and those which did not. While for the for-

mer, the MAD is decreasing with experience, for the latter it is increasing ! The figure also illustrates the difference between the opening call auction and the continuous market. At the first replication there is no pronounced difference between the two. But at the fourth replication, for the cohorts which faced strong and explicit incentives the MAD is lower for the continuous market prices than for the call market prices. This does not mean that the continuous market is a better trading system than the call market. Rather it reflects that prices established in the continuous market benefit from the price discovery and learning process achieved previously in the opening call market. This experimental finding is in the line of the analysis of field data by Amihud and Mendelson (1987 and 1991).

5.2 Error correction from the preopening to the opening

Casual observation of the actions of the subjects in the lab suggests their behaviour could be approximated by the following heuristic rule: On observing an initial preopening price above 240, agents having observed the signal “not 490” react to this mispricing by placing sell orders, in order to trade at hopefully advantageously high prices. Symmetrically, on observing an initial preopening price below 240, agents having observed the signal “not 50” react to this mispricing by placing buy orders, thus trying to trade at advantageously low prices. This behaviour (which is in the spirit of the equilibrium strategies characterized in Proposition 2) leads to large supply, generating decreases from the preopening price (P_p) to the opening price (P_o): $P_o - P_p < 0$, when the former is overpriced ($v - P_p < 0$), and large demand, generating price increases, when the preopening price is below the true value of the asset.⁸

Note that this is indeed what happened in the two replications illustrated in Panels A and B of Figures 1 and 5. In both cases the value of the asset was 240. In Figure 1 the preopening price was above 240, supply increased from the preopening to the opening, and the opening price was closer to 240 than the preopening price. Symmetrically, in Figure 5, the preopening price was below 240, demand increased from the preopening to the opening, and the opening price was closer to 240 than the preopening price.

To test whether this behaviour is systematically present in the data, we

⁸Note that such a pattern would emerge if the opening price was a conditional expectation of the value of the asset and the preopening price also but based on a coarser information set. It would also emerge if these prices were equal to conditional expectations plus independent noise.

run the following error–correction regression (which is in the same spirit as the partial adaptation model in Camerer (1987) and in Williams (1987)):

$$P_o - P_p = \alpha + \beta(v - P_p) + z.$$

Running the regression across cohorts would not have been practical, as only 9 cohorts participated in a market with a preopening period. On the other hand, as learning is really effective only when subjects face strong and explicit incentives, we focused only on the cohorts with such incentive schemes. Consequently, the regression is ran across 35 replications of the game.

Figure 7, plots the regression line and data points with $P_o - P_p$ on the vertical axis and $v - P_p$ on the horizontal axis. The corresponding estimates and t–statistics are in Table 4. Consistent with the above interpretation, the slope is significantly positive (also consistent with informationally efficient pricing is the fact that the intercept is not significantly different from 0).

5.3 Unbiasedness regressions based on opening and preopening prices

With rational expectations and risk neutrality, prices should be equal to unbiased expectations of the value of the asset. Hence, in unbiasedness regressions of values onto prices the intercept should be 0 and the slope 1. On the other hand, if, due to imperfect learning, prices are equal to the expectation of the value plus a noise term, the slope should be lower than 1. In the extreme case where the price is pure noise, the slope should be 0. Building on these remarks, Biais, Hillion and Spatt (1999) run unbiasedness regressions of closing prices (proxying value v) onto opening (or preopening) prices (P) in the Paris Bourse to characterize the informational efficiency of the latter:

$$v = \alpha + \beta P + z.$$

They find that, for opening prices, the slope of the unbiasedness regression is not significantly different from 1 in the case of the CAC 40 index, while it is significantly different from 0. Furthermore, for preopening prices, the slope, while positive (suggesting some information content) is lower than for opening prices (suggesting greater noise).

Our study offers an opportunity to run similar unbiasedness regressions on experimental data, and thus shed light on the external validity of experiments relative to the field. As in the case of the error correction model

discussed above, we ran the regression across replications of the game, rather than across cohorts using data with and without incentives. For the regression corresponding to opening prices, when there was no opening call, the opening price corresponds to the first transaction price of the continuous phase. Regressions concerning preopening prices only includes cohorts that traded in the market structure including a preopening period.

The corresponding estimates and standard errors are in Table 5, Panel A. Consistent with the hypothesis that the first transaction price is a conditional expectation of the value, the intercept is not significantly different from 0, while the slope is (and is not significantly different from 1, since the estimate is 1.36, while the standard error is .26). This result is similar to that obtained by Biais, Hillion and Spatt (1999) with field data.

For the case when the regressor is the preopening price, the results are in Table 5, Panel B. Consistent with the hypothesis that the preopening price is a conditional expectation of the value, the intercept is not significantly different from 0, and the slope is positive. On the other hand, the standard error (0.58) is so large that the slope estimate (0.88) is not significantly different from 0 or from 1. While this contrasts with the finding by Biais, Hillion and Spatt (1999) that towards the end of the preopening period the slope of the unbiasedness regression is significantly positive, both in the present experimental data and in the field data the estimate of the slope of the unbiasedness regression during the preopening is positive but lower than its opening price counterpart.

6 Conclusion

This paper analyzes deviations from or convergence towards equilibrium in an asset market similar to Plott and Sunder (1988). We consider three market structures: a pure continuous market, identical to the market analyzed in Plott and Sunder (1988), a call market followed by a continuous trading phase, and a market where there is a preopening period prior to the opening call and the continuous market. We also consider two incentives regimes, one in which subjects face strong and explicit incentives (as their exam grades directly reflect their profits in the game) and one in which they are simply instructed to maximize profits and complimented if they end up with large final wealth.

We find that strong and explicit incentives are necessary for convergence to equilibrium and price discovery. We also find that in the market structure

where there is a preopening period before the opening call auction deviations from equilibrium are less frequent. We suggest the following interpretation: By observing the outcome of the initial preopening period, the agents initiate learning about the equilibrium and discovery of the value of the asset. This helps them better deal with the relatively complex call market mechanism and conduct more efficient learning in the continuous trading phase. This is consistent with the view, held by market organizers, that the preopening period contributes to the efficient workings of the following opening call auction.⁹

In further research, it would be interesting to develop models of equilibrium discovery, in the spirit of fictitious play-beliefs based and adaptive learning (see e.g. Roth and Erev, 1995, and Armantier (1998)), adapted to the structure of the trading game analyzed in this paper, and to estimate and test them with the data generated in our experiments.

⁹This is also consistent with the empirical analysis of field data generated during the preopening, the following call and the continuous market in the Paris Bourse by Biais, Hillion and Spatt (1999).

Appendix 1: Proof of Proposition 2

The out-of-equilibrium beliefs supporting the equilibrium are the following: Confronted with an offer to sell at a price lower than 240, agents who received the signal “not 490” or “not 240” believe that the dividend is 50 (irrespective of what has been played previously in the game). Confronted with an offer to buy at a price larger than 240, players who received the signal “not 50” or “not 240” believe that the dividend is 490 (irrespective of what has been played before). If player i is confronted with a set of limit orders, $l \in L$, out of the equilibrium path, when considering to trade against order l , he relies, to update his own signal, only on the informational content of order l .

Denote U_i the utility function of agent i . Consider the case where agent i , has observed “not 490”. His equilibrium utility is:

$$\frac{1}{2}U_i(4 * 240 + 25000) + \frac{1}{2}U_i(4 * 50 + 25000).$$

- If i refused to trade, mimicking the equilibrium strategy of agents observing “not 240”, he would get the same utility as in equilibrium.
- What if agent i offers to sell at a lower price than 240 ? If they have observed “not 490” or “not 240”, the other agents believe that the state is 50, and consequently refuse to buy, which leaves i in the same situation as if he had followed his equilibrium strategy. For the agents who have observed “not 50”, it is a dominant strategy to accept to buy. This trade, however, results in losses for i , lowering his utility below its equilibrium level. Hence this strategy is dominated by the equilibrium strategy.
- What if agent i offers to buy, at a price lower than 240 ? Then the other agents believe that the dividend is 240 if they have observed “not 490”. If they have observed “not 240” they believe that the dividend is 490, while if they have observed “not 50” they believe that the dividend is 240 or 490. Hence, irrespective of their signal they refuse to trade. Consequently, this strategy does not yield a larger expected utility to i than the equilibrium.
- Finally consider the case where i offers to buy at a price larger than 240. Agents having observed “not 50” or “not 240” believe that the

dividend is 490, and consequently refuse to trade. Agents having observed “not 490” would sell to i resulting in losses for i , and lowering his utility below its equilibrium level. Consequently this strategy is strictly dominated by the equilibrium strategy.

Now turn to the case where the agent has observed “not 240”. His equilibrium expected utility is:

$$\frac{1}{2}U_i(4 * 490 + 25000) + \frac{1}{2}U_i(4 * 50 + 25000).$$

- What if the agent offers to sell at a price larger than 240 ? Then agents having observed “not 490” refuse to trade. Similarly agents having observed “not 240” refuse to trade (believing that the dividend is worth 50) as well as the agents having observed “not 50” (believing that the dividend is worth 240). This leads to the same expected utility as if i followed his equilibrium strategy.
- What if agent i offers to sell at a lower price than 240 ? If they have observed “not 490” or “not 240”, the other agents believe that the state is 50, and consequently refuse to buy, which leaves i in the same situation as if he had followed his equilibrium strategy. The agents who have observed “not 50” accept to buy. Now this results in lower utility for i than if he had followed his equilibrium strategy, since in this case the true value of the dividend is 490. Consequently this strategy is dominated by the equilibrium strategy.
- What if agent i offers to buy, at a price lower than 240 ? Then the other agents believe that the dividend is 240 if they have observed “not 490”. If they have observed “not 240” they believe the dividend is 490, while if they have observed “not 50” they believe that the dividend is 240 or 490. Hence, irrespective of their signal they refuse to trade. Consequently, this strategy does not yield a larger expected utility to i than the equilibrium.
- Finally consider the case where i offers to buy at a price larger than 240. Agents having observed “not 50” or “not 240” believe that the dividend is 490, consequently refuse to trade. Agents having observed “not 490” sell, resulting in losses for i , and lowering his utility below his equilibrium level. Consequently this strategy is strictly dominated by the equilibrium strategy.

Similar arguments apply to the case where the agent has observed “not 50”.

Consequently, the equilibrium strategy dominates (either strictly or weakly) the other strategies.

QED

Appendix 2: Instructions to the subjects, in the market with a call opening auction followed by a continuous trading mechanism.

In this trading game you will have the opportunity to buy and sell shares. The instructions of the game are below. If you follow them carefully and make good decisions you can win a considerable amount of bonus points.

You will play 4 replications of the trading game. At the beginning of each replication you will receive 25000 francs and 4 shares. During the game you will have the opportunity to place orders to buy or sell the shares. (You can sell more shares than you own, i.e., short sales are allowed). At the end of each replication, you will compute the value of your final wealth, equal to the sum of:

- your initial cash: 25000 F,
- minus the cost of your share purchases,
- plus the proceeds from your share sales,
- plus the final value of your portfolio.

The final value of your portfolio is equal to the number of shares you own at the end of the replication, multiplied by the final value of each share. The final value of the shares, at the end of each replication, is drawn randomly (and independently from the previous draws). It can be 490, 240 or 50, with equal probability: one third. For example, if your only trade was the purchase of one share at price 200, and the final value of the shares is 240, your final wealth is: $25000 - 200 + 1 \cdot 240$. Since you can sell more shares than you own, you can end up with a negative number of shares held at the end of the replication. For example, if you sold 6 shares at 100 each and the final value of the shares is 50, your final wealth is: $25000 + 600 - 6 \cdot 50$, given that you have sold 2 shares more than you owned.

At the beginning of each replication you will receive a private information (keep it secret, don't reveal it to the others !). If the value of the shares is 490, half the players know it is not 240, while the others know it is not 50. If the value of the shares is 240, half the players know it is not 490, while the others know it is not 50. If the value of the shares is 50, half the players know it is not 240, while the others know it is not 490.

Each replication of the trading game includes two phases:

First, you can place limit orders to buy or sell (up to 10 shares at each price), by writing them on a piece of paper. These orders are then aggregated

into supply and demand curves, crossed to determine the opening price, in a call auction. The opening price is set to maximize trading volume, as explained in class. This price, but not the orders, is announced publicly to the players. After this announcement, you receive execution reports, telling you which of your orders are filled. All limit sell orders placed at prices below or equal to the opening price are executed at this price. All limit buy orders placed at prices above or equal to this price are executed at the opening price. The remaining orders are not executed. For simplicity, they automatically cancelled after the opening call.

Second there is continuous market, which lasts 7 minutes, during which you will have the opportunity to:

- announce offers to sell or buy, which I will write on the board (to make life easier for me when I write the offers on the board, they are all for one share only, but you can place many offers),
- announce that you desire to trade with one of the offers available on the board, and which have not been executed yet;
- cancel or revise your offers when they have not been executed yet.

After the 4 replications, you will compute the sum of your final wealth during the game. To obtain the number of bonus points to be then added to your grade at the exam, subtract 92000 to this sum, and divide the result by 3000.

Table 1: Number of cohorts (and number of replications of the game these cohorts played) for the different incentive schemes and market structures.

Number of cohorts (of replications)	Continuous	Call	Preopening	Total
With strong and explicit incentives	3 (13)	3 (12)	3 (10)	9 (35)
Without	4 (22)	6 (22)	6 (25)	16 (69)
Total	7 (35)	9 (34)	9 (35)	25 (104)

Table 2: Regression across cohorts of the proportion of orders inconsistent with equilibrium (average across the replications of the game) onto predetermined variables.

(To facilitate interpretations the indicator variables take the value one when the characteristic is present, and when it is not they take a negative value such that the cross-sectional mean of the variable is 0. The adjusted R2 is 80%)

	Coefficient	t-stat
Constant	36.25%	44.15
Incentives	-10.85%	-7.77
Call	-2.57%	-1.89
Preopening	-8.46%	-6.36
v=240	0.21	2.95

Table 3: Regression across cohorts of the change in proportion of orders inconsistent with equilibrium (between the first two and

last two the replications of the game) onto predetermined variables.

(To facilitate interpretations the regressors (except the intercept) are defined such that the cross-sectional mean of the variable is 0. The adjusted R2 is 47%)

	Coefficient	t-stat
Constant	-3.5%	-2.17
Incentives	-15.88%	-4.53
Call	-1.92%	-0.61
Preopening	-7.32%	-1.7
v=240	0.37	2.64
First two replications	-1.12	-3.61

Table 4: Error Correction Regression

Regression, across replications of the game, of price change from the preopening to the opening call auction onto the difference between the value of the asset and the preopening price.

Variable	Coefficient estimate	t statistic
Constant	-9.25	-0.93
Value – Preopening price	0.23	4.34

Table 5: Unbiasedness regression

Panel A:
Regression across replications of the game of value onto first transaction price
(104 data points)

Variable	Coefficient estimate	Standard error
Constant	-56.74	64.44
First transaction price	1.36	0.26

Panel B:
Regression across replications of the game of value onto preopening price
(35 data points)

Variable	Coefficient estimate	Standard error
Constant	57.00	140.9
Preopening price	0.88	0.58

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Figure 1 Panel A : Supply and demand during the preopening call

(cohort 24, preopening+call+continuous market, explicit incentives, replication 1, $V=240$).

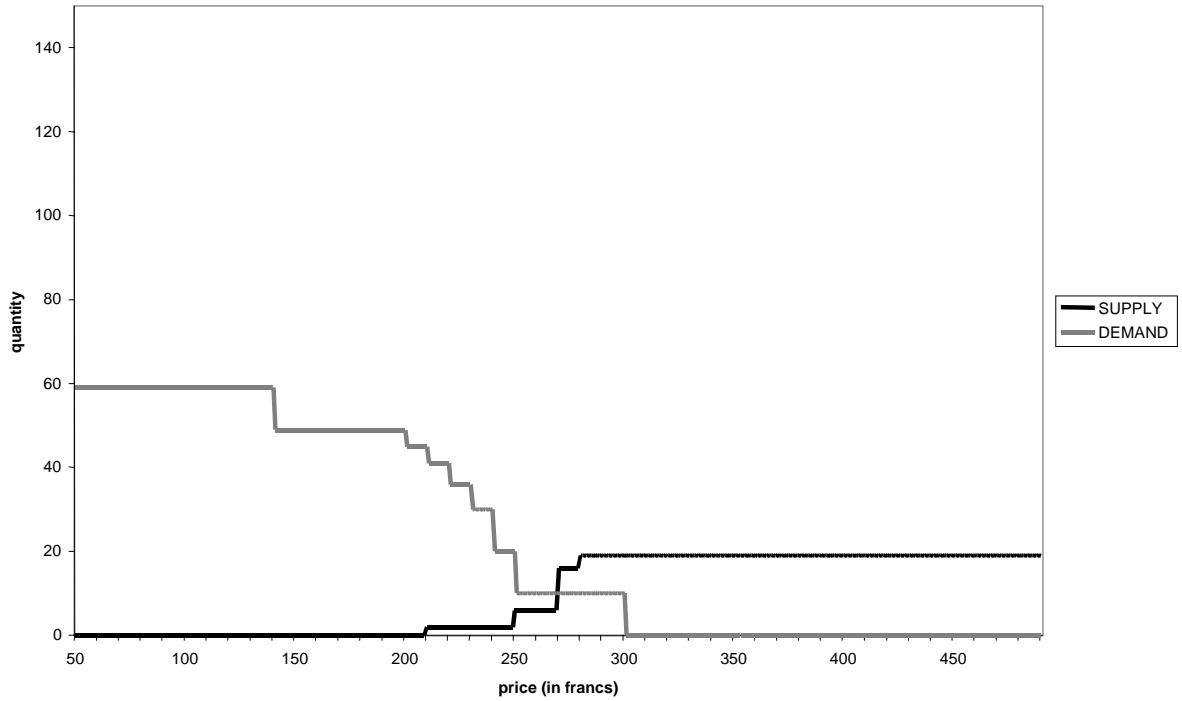


Figure 1 Panel B : Supply and demand during the opening call

(cohort 24, preopening+call+continuous market, explicit incentives, replication 1, $V=240$).

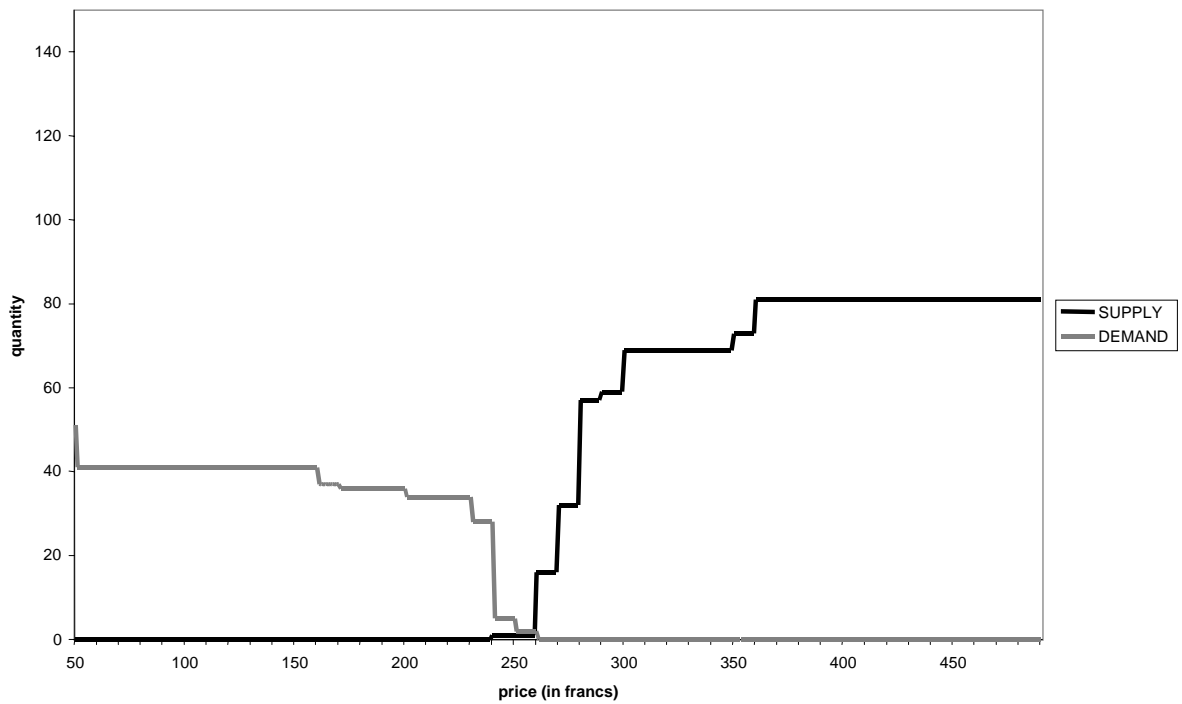


Figure 1 Panel C : Bid, ask and transaction prices during the continuous market
 (cohort 24, preopening+call+continuous market, explicit incentives, replication 1, $V=240$).

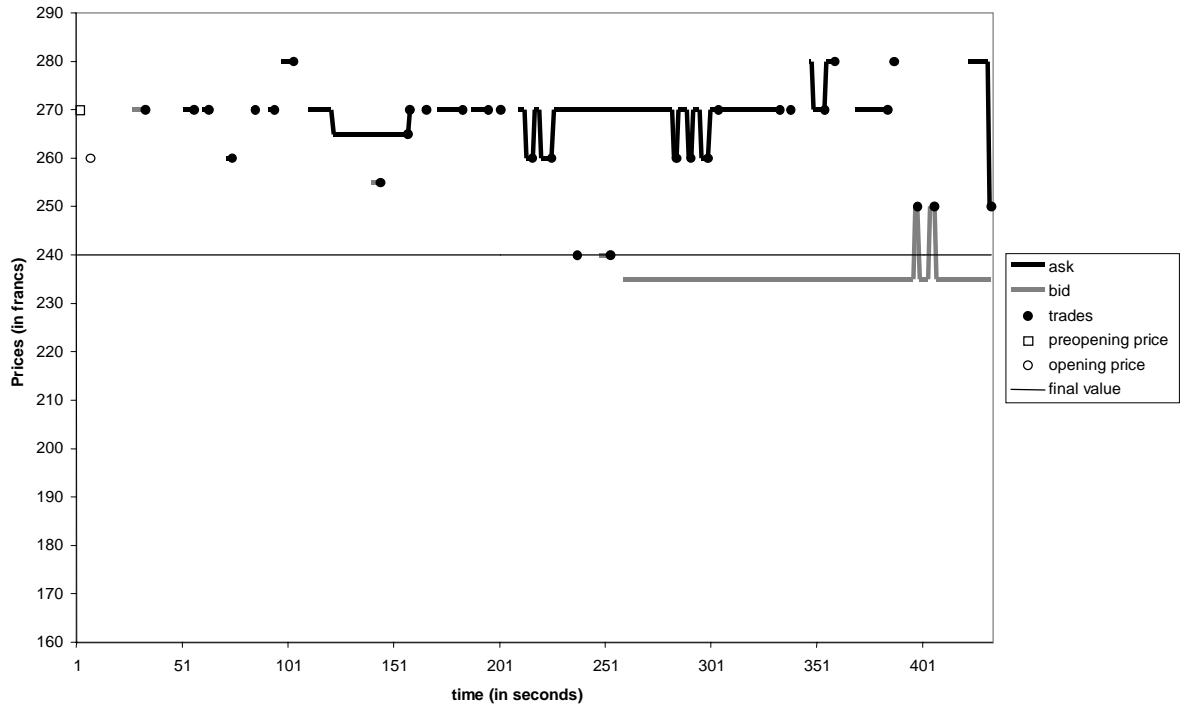


Figure 1 Panel D : Supply and demand during the preopening call
 (cohort 24, preopening+call+continuous market, explicit incentives, replication 3, $V=240$).

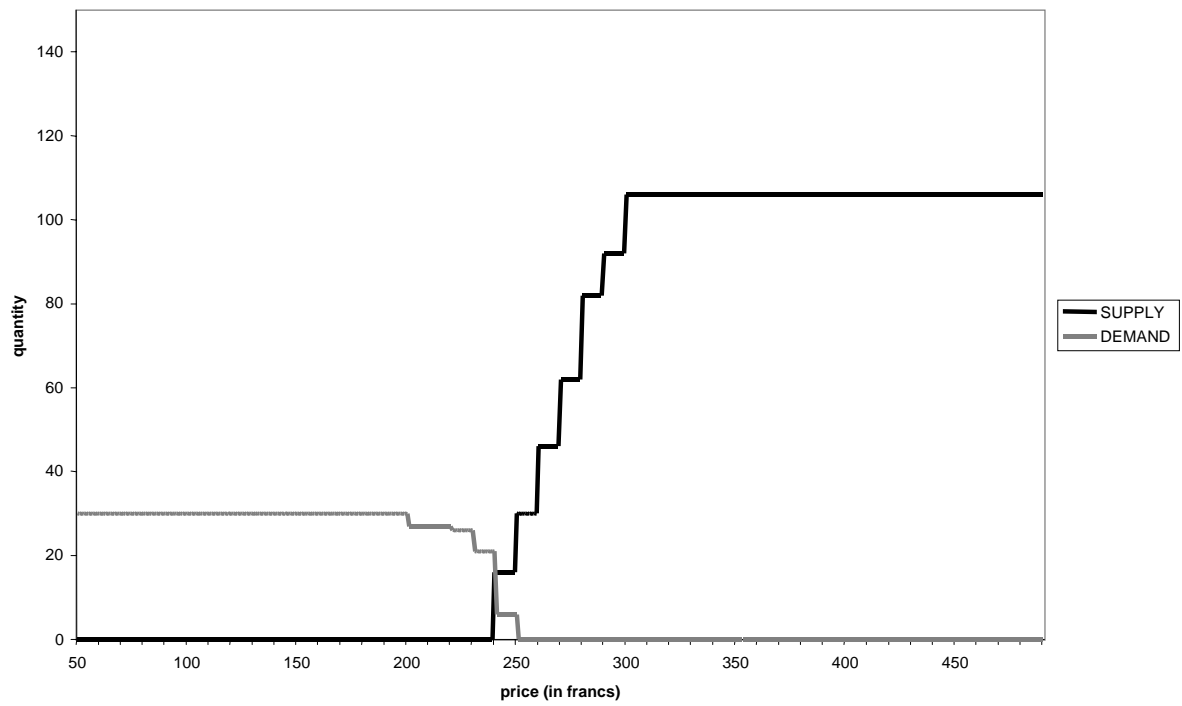


Figure 1 Panel E : Supply and demand during the opening call
 (cohort 24, preopening+call+continuous market, explicit incentives, replication 3, $V=240$).

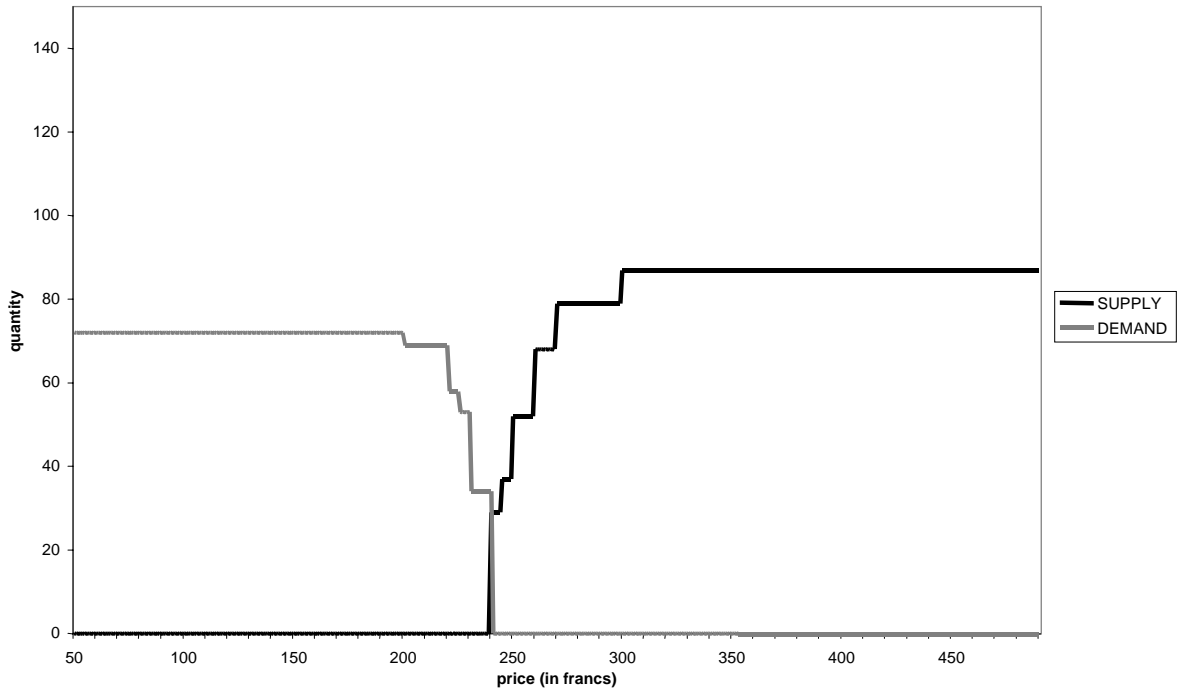


Figure 1 Panel F : Bid, ask and transaction prices during the continuous market
 (cohort 24, preopening+call+continuous market, explicit incentives, replication 3, $V=240$).

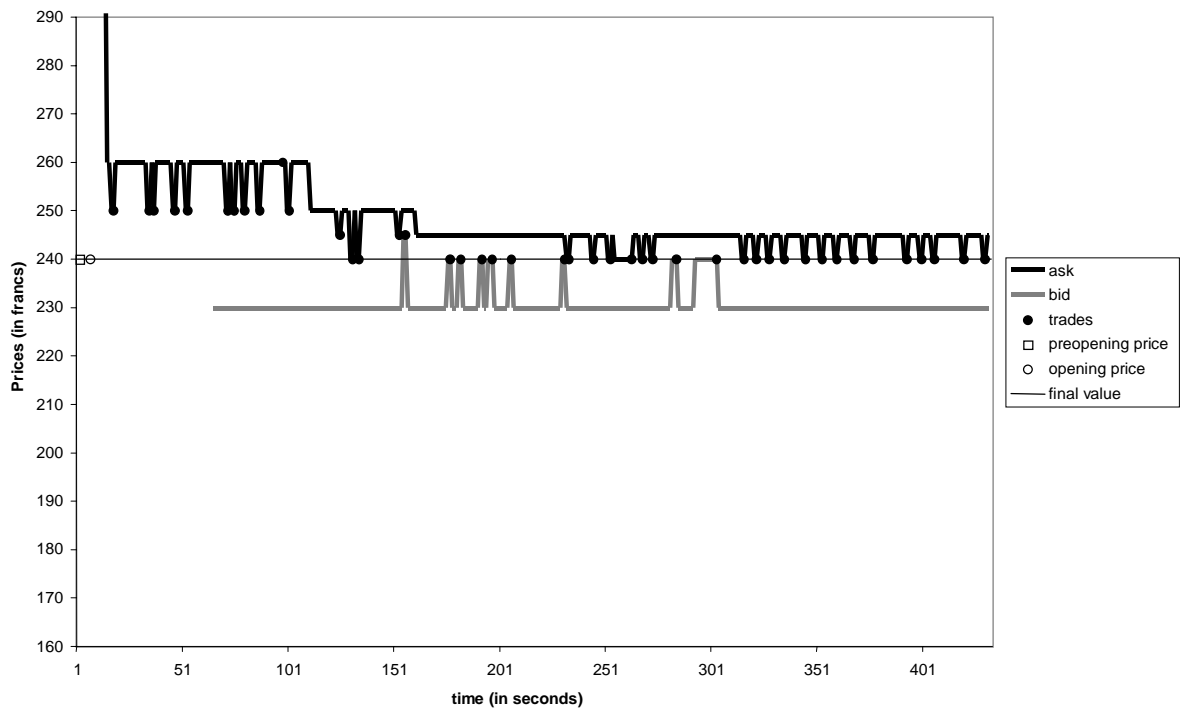


Figure 2 : Proportion of orders inconsistent with prior information.

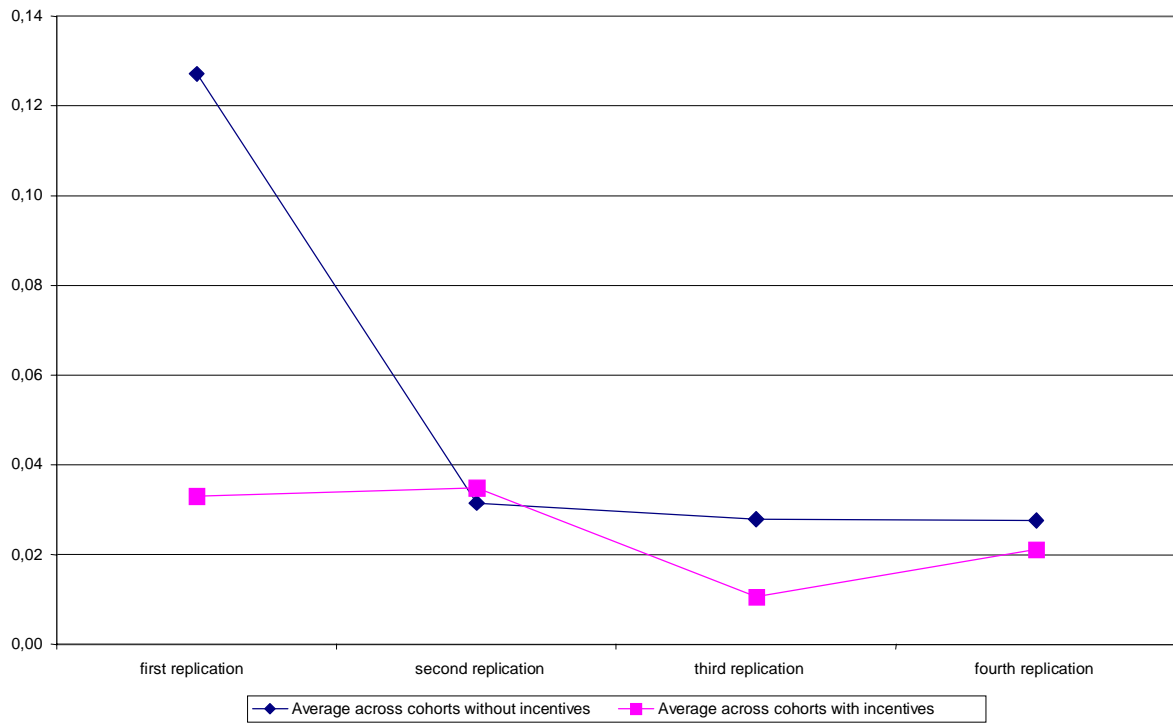


Figure 3 : Proportion of orders inconsistent with equilibrium
As a function of the structure of the market and of the incentives.

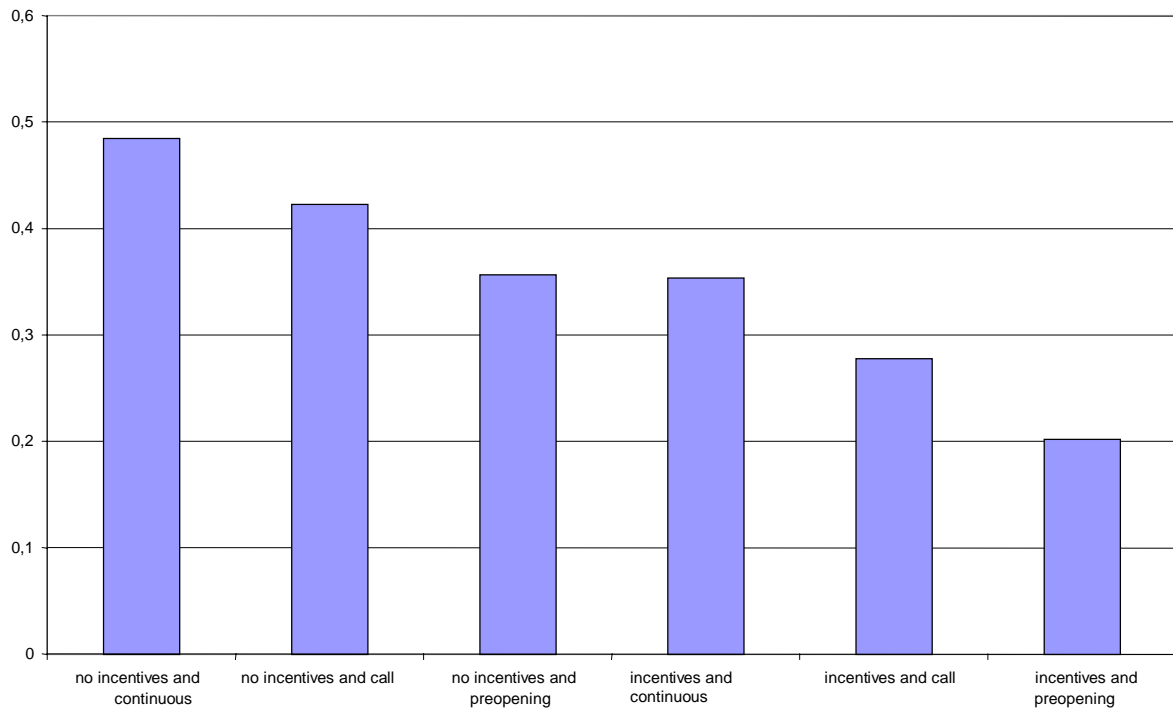


Figure 4 : Proportion of orders inconsistent with equilibrium.

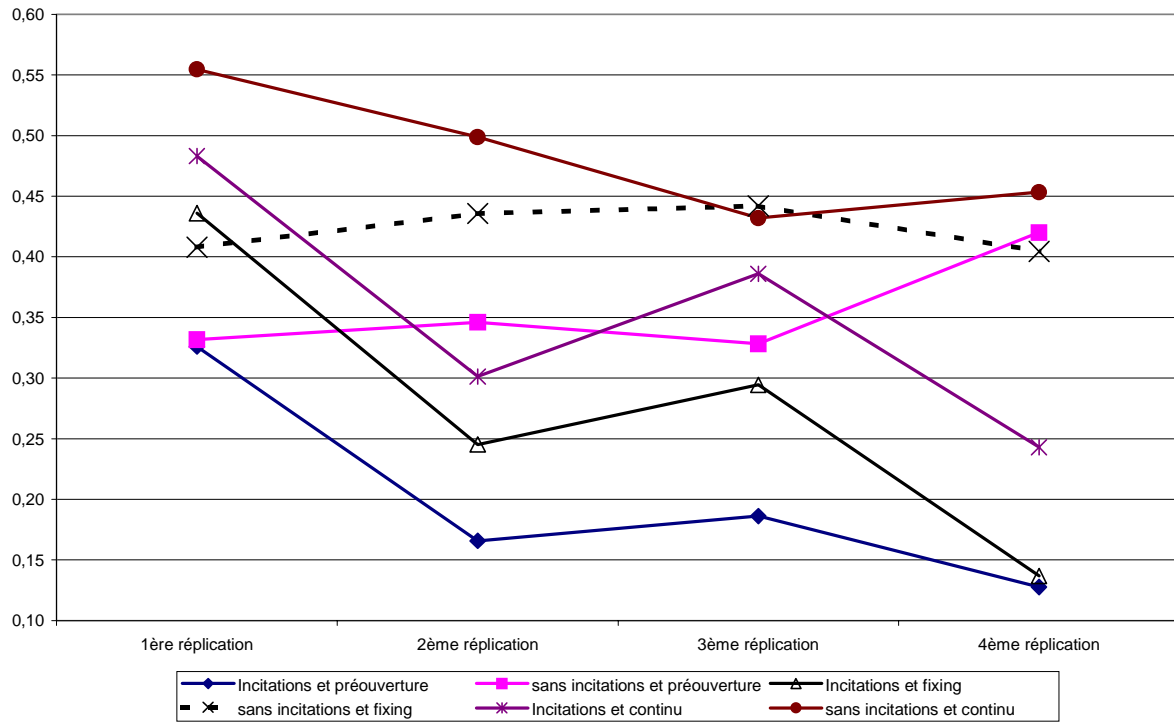


Figure 5 Panel A : Supply and demand during the preopening call
(cohort 28, preopening+call+continuous market, explicit incentives, replication 3, V=240).

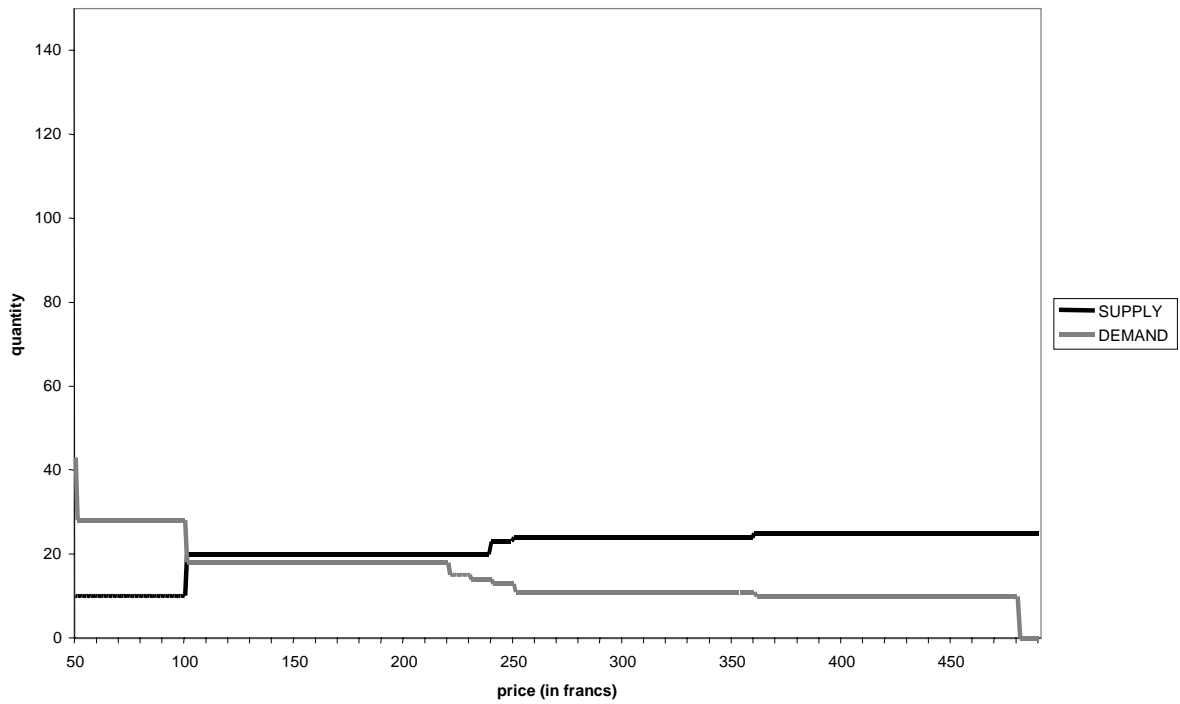


Figure 5 Panel B : Supply and demand during the opening call

(cohort 28, preopening+call+continuous market, explicit incentives, replication 3, $V=240$).

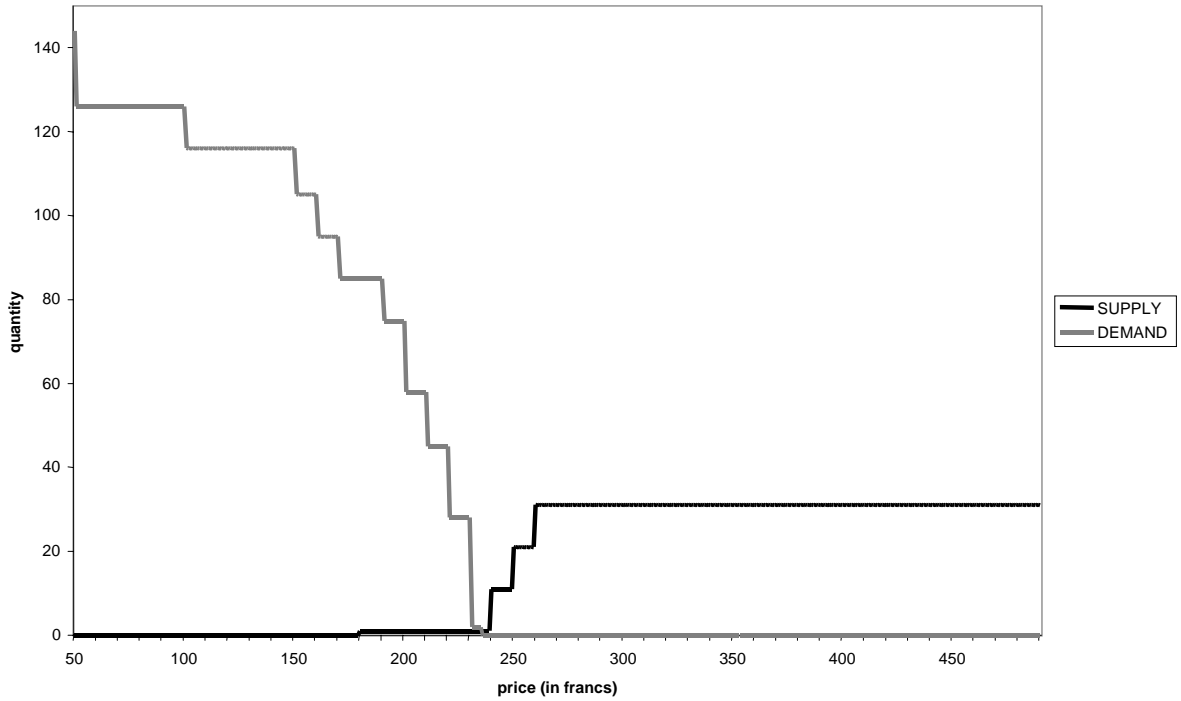


Figure 5 Panel C : Bid, ask and transaction prices during the continuous market

(cohort 28, preopening+call+continuous market, explicit incentives, replication 3, $V=240$).

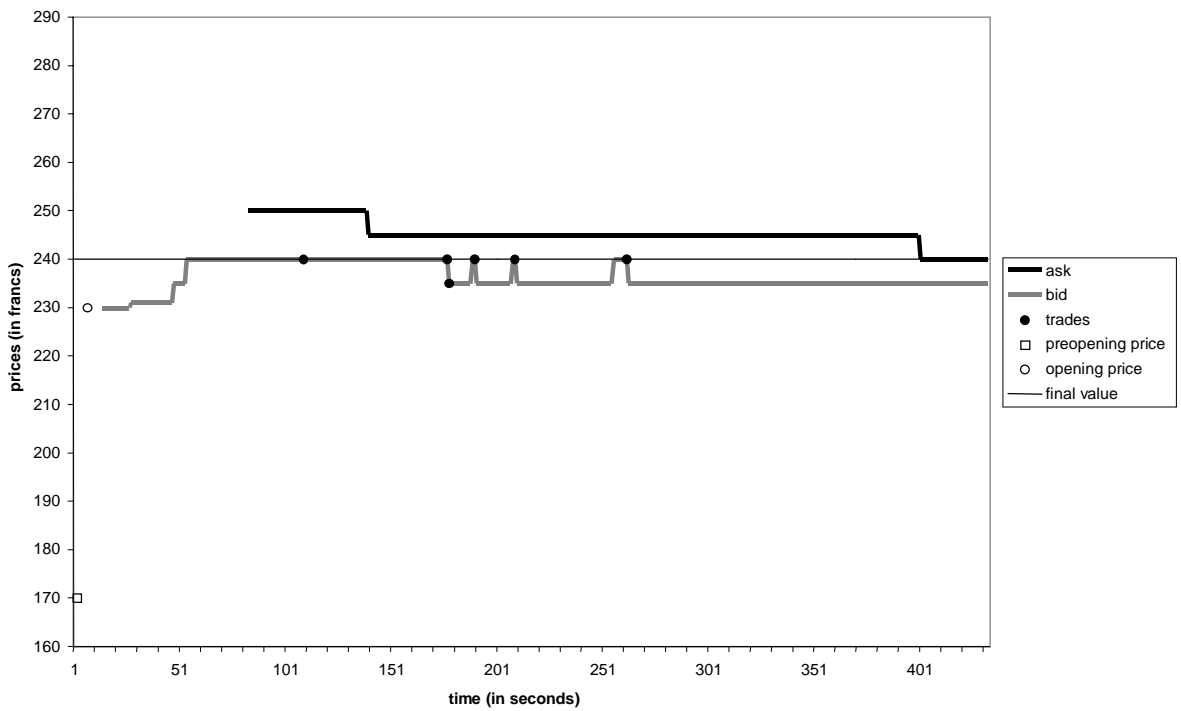


Figure 6 Panel A : Mean Absolute Deviation
 Between the opening call price and the true value of the asset.

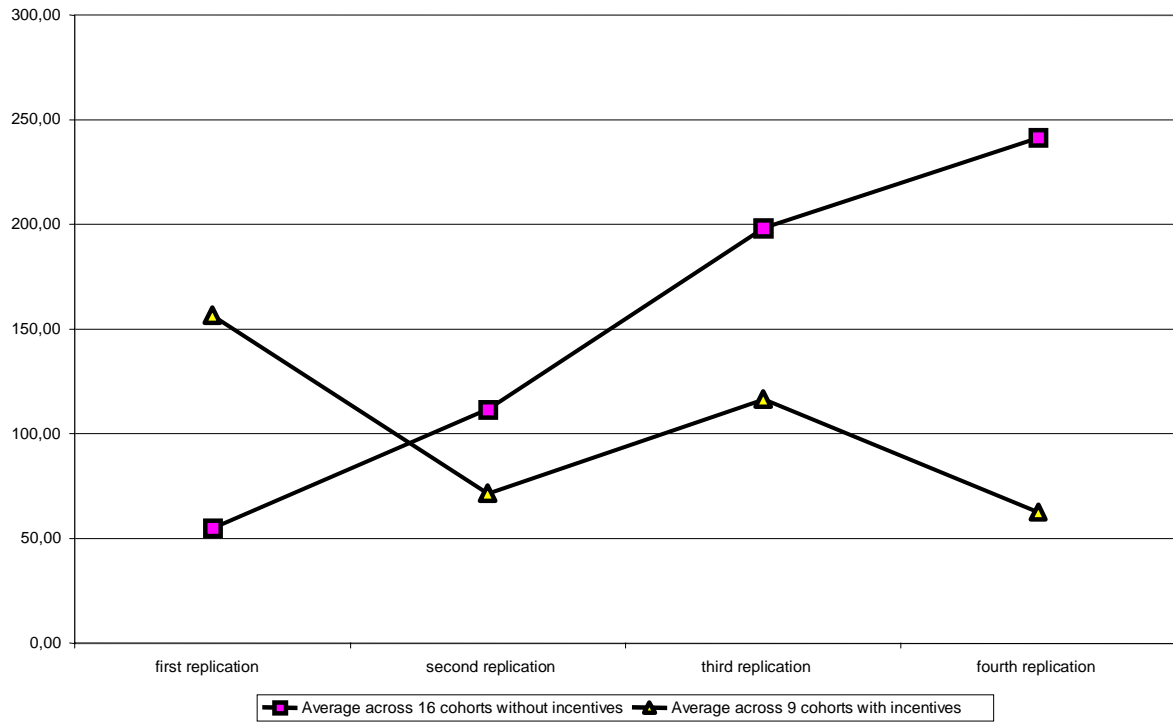


Figure 6 Panel B : Mean Absolute Deviation
 Between transaction prices in the continuous market and the true value of the asset.

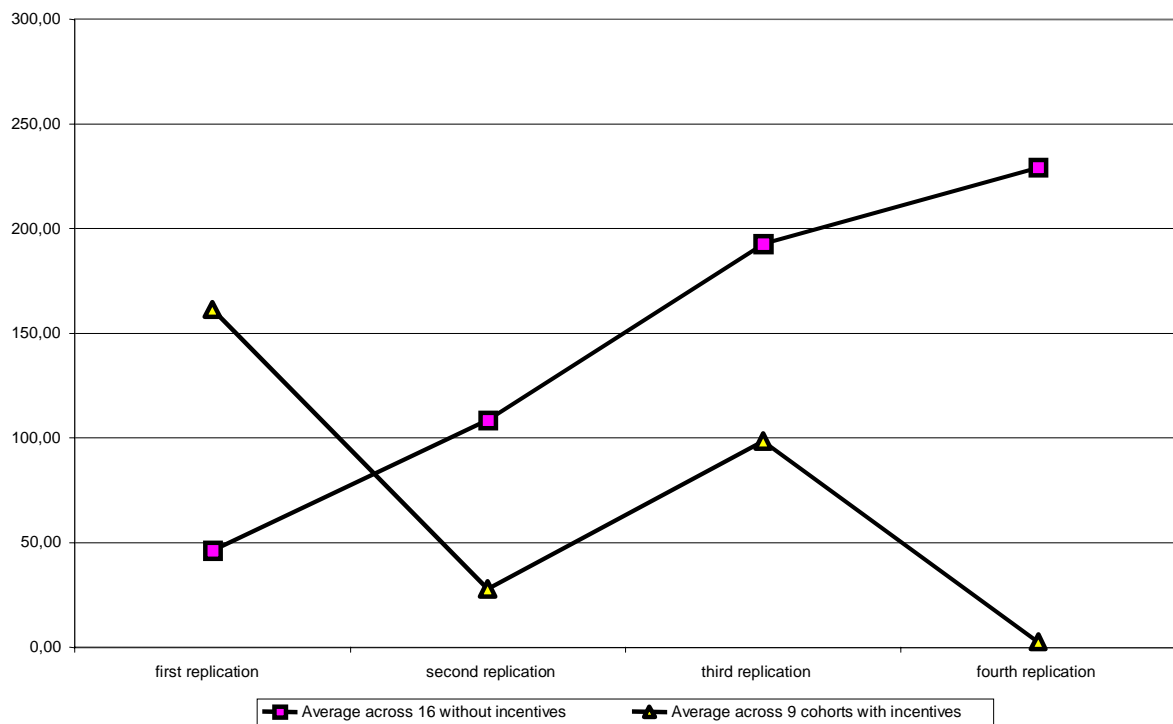


Figure 7 : Regression of the price adjustment between the preopening and the opening calls on the difference between the final value and the preopening indicative price (data with and without incentives).

