Private and Public Information in Common Value Multi-Unit Auctions

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Abstract

This paper aims at studying the interaction between private and public (inferred) information in the context of common value multi-unit auctions. We develop a theoretical model where different sources of information are available. We derive the equilibrium bidding strategies in this setting and set different testable hypothesis about the way strategies are affected availability of information. These hypotheses are then tested in lab experiments in which we consider three mechanisms: (i) simple auctions where participants only have private signal about the risky asset, (ii) simple auctions preceded by a market based information aggregation mechanism, and (iii) simple auctions are preceded by a pre-auction cheap-talk communication round. The outcome is consistent with the theoretical predictions and the fact that the market based information mechanism dominates simple auctions and cheap talk auctions. Finally, we discuss the application of such results in IPOs by proposing a new IPO procedure allowing alleviation of the adverse selection risk.

Key Words: Information aggregation, common value, Multi-unit auctions

JEL Classification: C92, D44, D82

1 Introduction

Common-value multi-unit auctions are a common institution. They are used to sell both financial asset such as Treasury bonds and newly issued shares, and other items such as competitive electricity pools and FCC spectrum. In these trading settings, public information plays a crucial role. In their seminal paper, Milgron and Weber (1982) show that more public information in affiliated value auctions, reduces the winner curse and lead to more agressive bidding and higher price on average. This has been the subject of multiple experimental studies (see Kagel and Levin, 2002, for a list of articles).

The objectives of this paper are twofold. First, we seek to study the impact of public information on equilibrium outcomes and bidding behavior in multi-unit common-value auction. Second, we seek to explore ways to improve public information and increase market transparency in these settings. From a normative point of view, the latter objective is of great importance. The recent scandals related to financial information disclosure led to an obsessive supervision of market transparency by financial markets regulators. A direct way to increase market transparency is by implementing rules making all information available for different market participants. Enforcing these rules may however be very complex; hence, the need to propose mechanisms allowing better information transmission between agents. To which extent these mechanisms can achieve their role of increasing the level of public information available to agents? And more importantly, how public information acquired by agents will interact with their private information and affect their trading strategies? To address these questions is among the objective of this work. However, we cannot pursue the second objective without addressing the first one. In order to compare different mechanism seeking to improve public information, we must be able to measure the quality of the additional public information through its impact on equilibrium outcomes and bidding behavior in multi-unit common-value auction.

We begin by constructing a theoretical model in which the interactions of private and public information and their impact on the trading behaviour of subjects are analyzed. Then in order to test the theoretical results, we design a laboratory experiment in which trading outcomes and the strategic behaviour of different subjects in various settings are compared. The experimental treatments are distinguished according to two dimensions: the quality of the private information and the availability and nature of source of public information. More precisely, three different settings are compared: auctions preceded by a market-based information aggregation mechanisms (hereafter, IAM), auctions preceded by a cheap talk round between subjects, in which they can share their information, and finally simple auctions without pre-auction communication. In the first pre-auction communication setting, agents may exchange an asset whose value is related to the one to be sold in the simple auction. This double auction market is intended to allow traders to get some information from different transactions they observe in this market. The second mechanism is a cheap talk mechanism in which participants are allowed to announce the value of their signal before they are asked to submit their demand functions. They may however either announce truthfully their signal or cheat.[1] In this respect our work is also related to Information Aggregation Mechanisms literature. Indeed, by adding the market based mechanism as well as the cheap talk mechanism, we create mechanisms intended to aggregate information hold by market participants. Whether these mechanisms reach their goals of allowing higher information transmission among market participants and consequently a better convergence of prices to the true values of assets is another question that is addressed in this paper.

A serie of papers and real life experiments suggest that markets when properly designed can be useful "Information Aggregation Mechanisms", henceforth IAM. Prices, especially in financial markets, reflect, if not all, a large proportion of the information held by the market participants. If one thinks that an asset is underpriced, he should buy more of this assets and eventually push the price up, inversely, if one thinks the asset is overpriced, he should sell it. Hence, informed agents have the incentive to share part of their information through the market. In a thick and competitive market, prices will tend to be very informative. This principle was successfully exploited by the Iowa Electronic Markets in order to forecast election results. Chen and Plott (2002) report on the use of an IAM in a business environment to forecast sales at

[1] This may be seen as a measure of the efficiency of cheap talk mechanisms with respect to market based mechanisms as a way to achieve efficient equilibria (Crawford (1998), Farrel and Rabin (1996) and Duffy and Feltovich (2002)).

HP. The conclusion of this litterature is that an IAM can be useful in various contexts where information is both dispersed and strategically key. Our study adds to the existing literature. Our focus is not on the IAM as a predictive device but as a decision tool, and its impact on market participants' strategies. This may be seen as a way to study a decision market while Chen and Plott (2001) focused on predictive markets.[2]

Our paper is also related to the literature studying efficiency and trading behaviour in auctions (Kagel and Levin (2001), Engelmann and Grimm (2002) and Parlour et al. (2003)). As for this literature, we study the bidding behaviour of agents in a multi-unit auction setting. We do however focus on analyzing the interactions of information within agents by studying the effects of private, the inferred (from the observed actions in the market) and public information on the strategic trading of agents.

We find that our experimental data confirms the theoretical predictions of the model. Moreover, we find that market based IAMs permit a higher informtion transmission between agents than both simple auctions and cheap talk auctions. These results may be applied to propose a new IPO mechanism aiming to alleviate information asymmetry between different participants in an IPO. A lare literature has discussed the relative merits of bookbuilding and auctions procedures for IPOs (see among others Derrien and Womack,2003; Biais and Fougeron-Crouzet, 2002; Sherman, 2000). Bookbuilding is a selling procedure based on a collection, by underwriters, of indications of interest from institutional investors that may help the issuers to set the IPO price. These indications of interest are non binding which makes bookbuiding similar to a cheap talk mechanism. Our result suggest that an IPO mechanism using a market based IAM dominates the existing machanisms, at least as an information mechanism allowing lower adverse selection risk.

The paper is organized as follows. In the next section, we present our theoretical model. Using numerical simulations, we show how the equilibrium bidding behavior varies with the quality of the private and public signals available to the participants. In Section 3, we present

[2] Decision markets are those where the gathered information is used to take decision. Predictive markets are those used to make more accurate predictions about a future event (for more details see Berg et al. (2001) and Hanson (1999).

our experimental design. Basically, subjects are invited to participate in multi-unit common value auction under different information settings. In Section 4, we examine the experimental data. We estimate, in particular the demand curves submitted by the subjects and examine the impact of information on bidding behavior. In section 5, we propose an IPO application for our results and discuss the implementation issue of the new IPO mechanism. Some concluding remarks as well as a recap of our results are provided in section 6.

2 A theoretical model

In this section, we develop a game-theoretical model where n bidders participate in a multi-unit common-value auction. The auctioneer puts on sale Q units of a risky asset. The value of the risky asset is denoted by θ. This value is random and remains unknown to bidders before the auction. However, each bidder holds some information about θ. Each of them submits a demand function. The auctioneer then find the price such that total demand in equal to the quantity supplied Q.

As in Kyle (1989), the equilibrium we consider is the rational expectation equilibrium with imperfect competition among agents. We consider here a class of equilibria in which bidders submit downward slopping demand curves. The main difference between our model and Kyle's model is that, in our model, bidders do not only observe a private signal about the value of θ, but also observe a common public signal, which is itself an imperfect signal of the aggregate individual private signals. Our model allows us to explore how the bidding behavior and equilibrium price outcome vary with the quality of this public signal and hence examine the impact of information aggregation and market transparency. In the end of this section, we perform some comparative statics through numerical simulations.

2.1 The model

We assume that each bidder i receives, prior to bidding, two imperfect signals about the value of the risky asset, θ. The first signal is denoted by s_i, it is a private signal for i. The second signal, denoted by S, is a public signal observed by all. Both signals are noisy and all random variables are assumed normally distributed. So, we suppose that

$$s_i = \theta + t_i \quad \text{where} \quad \theta \sim N(\bar{\theta}, \sigma_\theta^2) \quad \text{and} \quad t_i \sim N(0, \sigma_t^2) \tag{1}$$

and

$$S = \sum_j s_j + \mu = n\theta + \sum_j t_j + \mu \;\; \text{where } \mu \sim N(0, \sigma_\mu^2) \tag{2}$$

Note that S is a noisy signal of all private signals received by bidders. If $\sigma_\mu^2 \to 0$, it is as if participants could basically observe the signal of all others, this would correspond to the case where bidders have access to a perfect Information Aggregation Mechanism. Alternatively, if $\sigma_\mu^2 \to \infty$, we have $E(\theta|S, s_i) = E(\theta|s_i)$, i.e. bidders can infer no additional information about the final value of the asset from observing S. By changing the value of σ_μ^2 we will explore the impact of information aggregation and market transparency on market equilibrium and bidding strategies.

We also suppose that participants have CARA preferences with r denoting their risk aversion coefficient. Under the assumption of normal distributions, it implies that preferences can be represented using the mean-variance representation. The expected utility of a bidder who receives a quantity $q_i = x$, has the expected utility given by:

$$E_\theta \left[W + \theta(x + \epsilon_i) - p(S, s)x | S, s_i, q_i = x \right] - rVar\left[\theta | S, s_i, q_i = x\right] (x + \epsilon_i)^2 \tag{3}$$

where W is some initial wealth and ϵ_i corresponds to an idiosyncratic liquidity shock that agent i receives before participating in the auction. We assume that ϵ_i is private information to i and follows distribution $N(0, \sigma_\epsilon^2)$. The introduction of ϵ_i adds a second motivation for trading as in Glosten (1989). This noise will make the rational expectations equilibrium partially revealing and, by doing so, may be considered as an alternative solution to the Grossman and Stiglitz (1980) paradigm related to the fully revealing rational expectations equilibria.[3] Indeed, observing a higher demand by an agent may be interpreted either because of a good information or because of a large negative liquidity shock for the risky asset.

[3] See Biais and Rochet (1996) for more details about these different treatments of noise introduced in order to deal with the Grossman and Stiglitz paradigm.

2.2 Equilibria with linear downward sloping demand

For tractability, that bidders can submit negative demand. Under this assumption and simplifying assumptions of normal and independent noises and CARA utility function, we are able to compute a rational expectation symmetric equilibrium with downward sloping demand curves. The equilibrium is derived by maximizing each agent's expected utility against the residual demand curve. Indeed, in the spirit of rational expectations equilibria, after making conjectures about the optimal demand functions of his competitors, each agent will choose his optimal strategy by acting as a monopsonist with respect to a residual demand curve representing the demand functions of his competitors.

More precisely, we are looking for a set of bidding functions (or demand functions), $\{x_i(p, s_i, S, \epsilon_i)\}_{i=1}^n$, which forms a rational expectation equilibrium. Let $Y_i(S, p, x_i(\circ))$ denote the subset of all possible private information held by others which is consistent with an equilibrium price p whenever i submits the demand function $x_i(\circ)$. In equilibrium, for each agent i, his demand function, $x_i(p, s_i, S, \epsilon_i)$, maximizes his expected utility given his private information, s_i, the public signal, S, and $Y_i(S, p, x_i(\circ))$,the indirect information that he can infer from the others' strategies and the resulting equilibrium price and quantity.

So, in a first step, let us suppose that agent i conjectures that each agent $j \neq i$, has the following inverse demand function :

$$p(x_j, S, s) = a + bs_j - cx_j + dS - h\epsilon_j \tag{4}$$

where s is the vector of all agents' private signals. Since, the equilibrium price would be the same for all agents, summing the demand functions for all $j \neq i$ and adding the market clearing conditions yields:

$$p(x, S, s) = -\frac{c}{(n-1)}(Q - x_i(s_i, p)) + a + \frac{b}{(n-1)}\sum_{j\neq i} s_j + dS - \frac{h}{(n-1)}\sum_{j\neq i}\epsilon_j \tag{5}$$

Then given these conjectures, the information one can infer from a given inverse demand function is given by:

$$Y_i(S,p,x_i(p,\circ)) = \left[\{(s_j,\epsilon_j)\}_{j\neq i}\middle| y = \left[-\frac{c}{(n-1)}(Q - x_i(s_i,p)) + a + dS\right]\right]$$

$$\text{where } y = \left[\frac{b}{(n-1)}\sum_{j\neq i} s_j - \frac{h}{(n-1)}\sum_{j\neq i}\epsilon_j\right] \tag{6}$$

Basically, a participant can infer y from the equilibrium price and quantity. From any inverse demand function, one can infer one and only one y. The variable y is normally distributed and correlate with the public signal S. Note that when the variance of ϵ_j, σ_ϵ^2, goes to zero, then $y = \left[\frac{b}{(n-1)}\sum_{j\neq i} s_j\right]$ and the market equilibrium is fully informative. Under the rational expectation equilibrium, the bidder should set his optimal demand function using the conditional distribution of θ given (s_i, S, y). In the following lemma, we characterize this distribution.

Lemma 1 *Consider the triplet of variables (s_i, S, y), normally distributed and defined as follows :*

1. $s_i = \theta + t_i$ *where* $\theta \sim N(\bar{\theta}, \sigma_\theta^2)$ *and* $t_i \sim N(0, \sigma_t^2)$
2. $S = \sum_j s_j + \mu = n\theta + \sum_j t_j + \mu$ *where* $\mu \sim N(0, \sigma_\mu^2)$
3. $y = \left[\frac{b}{(n-1)}\sum_{j\neq i} s_j - \frac{h}{(n-1)}\sum_{j\neq i}\epsilon_j\right]$ *where* $\epsilon_j \sim N(0, \sigma_\epsilon^2)$

then θ given (s_i, S, y) is normally distributed with :

$$E\left[\theta|y,S,s_i\right] = \left(\frac{k_0}{k}\right)\overline{\theta} + \left(\frac{k_1}{k}\right)\left(\frac{y}{b}\right) + \left(\frac{k_2}{k}\right)\frac{(S-s_i)}{(n-1)} + \left(\frac{k_3}{k}\right)s_i \tag{7}$$

$$\text{and } Var(\theta|y,s_i,S) = \sigma_t^2 k_3 \tag{8}$$

where

$$k_0 = \sigma_t^2 \tag{9}$$

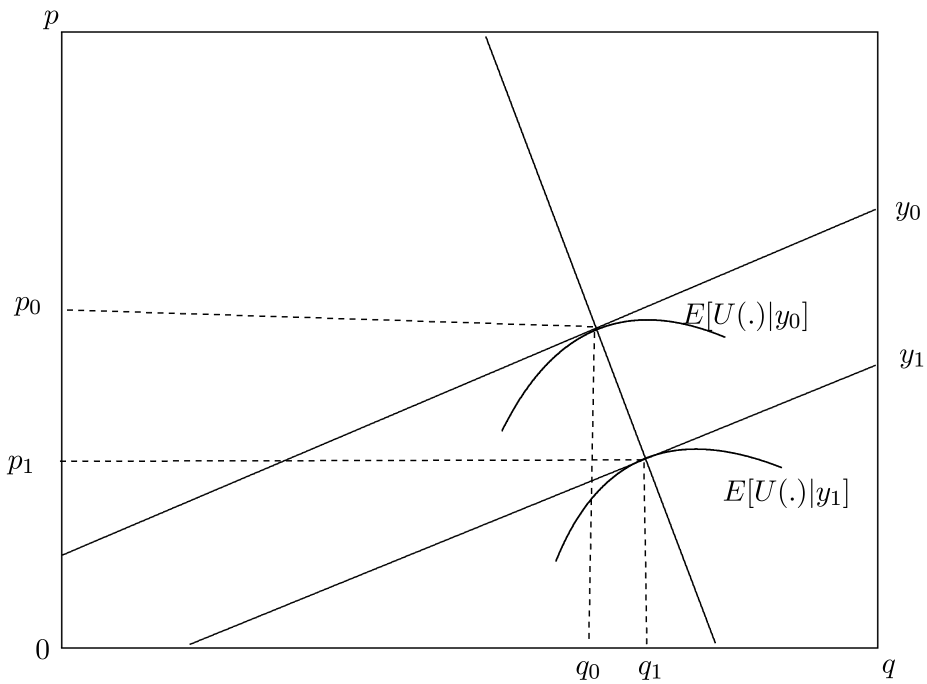
$$k_1 = \frac{(n-1)\,b^2\sigma_\theta^2\sigma_\mu^2\sigma_t^2}{[h^2\sigma_\varepsilon^2\sigma_\mu^2 + b^2\sigma_t^2\sigma_\mu^2 + (n-1)h^2\sigma_\varepsilon^2\sigma_t^2]} \tag{10}$$

$$k_2 = \frac{(n-1)^2h^2\sigma_\theta^2\sigma_\varepsilon^2\sigma_t^2}{[\sigma_t^2h^2\sigma_\varepsilon^2(n-1) + h^2\sigma_\varepsilon^2\sigma_\mu^2 + \sigma_t^2b^2\sigma_\mu^2]} \tag{11}$$

$$k_3 = \sigma_\theta^2 \tag{12}$$

$$\text{and } k = [k_0 + k_1 + k_2 + k_3] \tag{13}$$

Figure 1: construction of bid functions



The proof of Lemma 1 is both standard and tedious. Hence, it is omitted. The results are overall quite standard, the conditional expected value of θ is a convex sum of the observed variables and their weights depend on the respective quality of the signals and correlation. Some interesting intuitions may be derived from the different parameters defining the conditional expected value. For example, if $\sigma_\epsilon^2 \to 0$, then $k_2 = 0$, in this case, the equilibrium price is fully revealing and the public signal is valueless. Altenatively, when $\sigma_\epsilon^2 \to \infty$, then $k_1 = 0$, the observation contains in y is valueless. Similar results may be derived by changing the value of σ_μ^2, which measures the magnitude of the noise attached to the public signal .When σ_μ^2 is high, the public signal is very noisy and less useful.

Let us now turn to the derivation of the equilibrium. Figure 1 illustrates how a bidder should construct his optimal bid. Suppose that a bidder faces a given residual demand curve associated with some y_0. The bidder can select the pair (p_0, q_0) lying along this curve and which maximizes his expected utility given s_i, S, and y_0. He can do so by proposing any demand curve that passes on this point. In doing so, he maximizes his expected outcome whenever $y = y_0$. Now suppose that $y = y_1$ instead and that the bidder faces a given residual demand curve associated with some y_1. He must then select the pair price and quantity (p_1, q_1) lying along this new residual demand curve and which maximizes his expected utility given that $y = y_1$. Again, he can maximize his expected outcome whenever $y = y_1$, by submitting a demand curve that passes through this point. Accordingly, the best response by the bidder is to submit a demand curve that connect all the optimal price-quantity for all possible y.

Formally, if a bidder faces a residual inverse demand curve of the form:

$$p(Q-x,y) = -\frac{c}{(n-1)}(Q-x) + a + dS + y \tag{14}$$

given some y, then his optimal demand is the one solving the following problem :

$$\begin{array}{l} \max_x \{W + (x+\epsilon_i)E(\theta|s_i, y, S) \\ -\left[-\frac{c}{(n-1)}(Q-x) + a + dS + y\right](x+\epsilon_i) - \frac{r}{2}(x+\epsilon_i)^2 Var(\theta|y, s_i, S)\right\} \end{array} \tag{15}$$

The first order condition is

$$0 = E(\theta|s_i, y, S) - \left[-\frac{c}{(n-1)}(Q-x) + dS + a + y\right] - \left(\frac{c}{(n-1)} + rVar(\theta|y, s_i, S)\right)(x+\epsilon_i) \tag{16}$$

and the second order condition is then :

$$\frac{2c}{(n-1)} + rVar(\theta|y, s_i, S) > 0 \tag{17}$$

If we connect all the pairs price-quantity corresponding to each of the above solutions for all y, then we obtain a linear demand curve that depends on the parameters a, b, c, d, h and k_0, k_1, k_2 and k_3.

Proposition 2 *For strictly positive $r, \sigma_\varepsilon^2, \sigma_\theta^2$, σ_μ^2,and σ_t^2 , and $n > 2$, there exists a rational expectation equilibrium where each bidder submits a strictly decreasing inverse demand curve of the form:*

$$p(x) = a + bs_i + dS - cx - h\epsilon_i$$

and where:

$$a = k_0\overline{\theta} + \left(\frac{k_1}{(n-2)k_3 - \frac{(n-2)k_2}{(n-1)} - 2k_1} \right) r\sigma_t^2 \left(\frac{k_3}{k} \right) Q \tag{18}$$

$$b = \left(\frac{k_3}{k} - \frac{k_2}{k(n-1)} + \frac{k_1}{k} \right) > 0 \tag{19}$$

$$c = \left(\frac{(n-1)\left(k_3 - \frac{k_2}{(n-1)} + k_1\right)}{(n-2)k_3 - \frac{(n-2)k_2}{(n-1)} - 2k_1} \right) r\sigma_t^2 \left(\frac{k_3}{k} \right) > 0 \tag{20}$$

$$d = \left(\frac{k_2}{k(n-1)} \right) > 0 \tag{21}$$

$$h = \left(\frac{k_3 - \frac{k_2}{(n-1)} + k_1}{k_3 - \frac{k_2}{(n-1)}} \right) \left(\frac{(n-1)k_3 - k_2 - k_1}{(n-2)k_3 - \frac{(n-2)k_2}{(n-1)} - 2k_1} \right) r\sigma_t^2 \left(\frac{k_3}{k} \right) > 0 \tag{22}$$

and k, k_0, k_1, k_2 and k_3 are defined in lemma 1.

The proof is in Appendix A.

Although we cannot derive a simple closed form solution for the equilibrium, we can compute it numerically. Notice that the value (b/h) enters into the calculation of the k's. Using the fact that:

$$\left(\frac{h}{b} \right) = \frac{[k_3 - \frac{k_2}{(n-1)}]}{r\sigma_t^2 k_3} \tag{23}$$

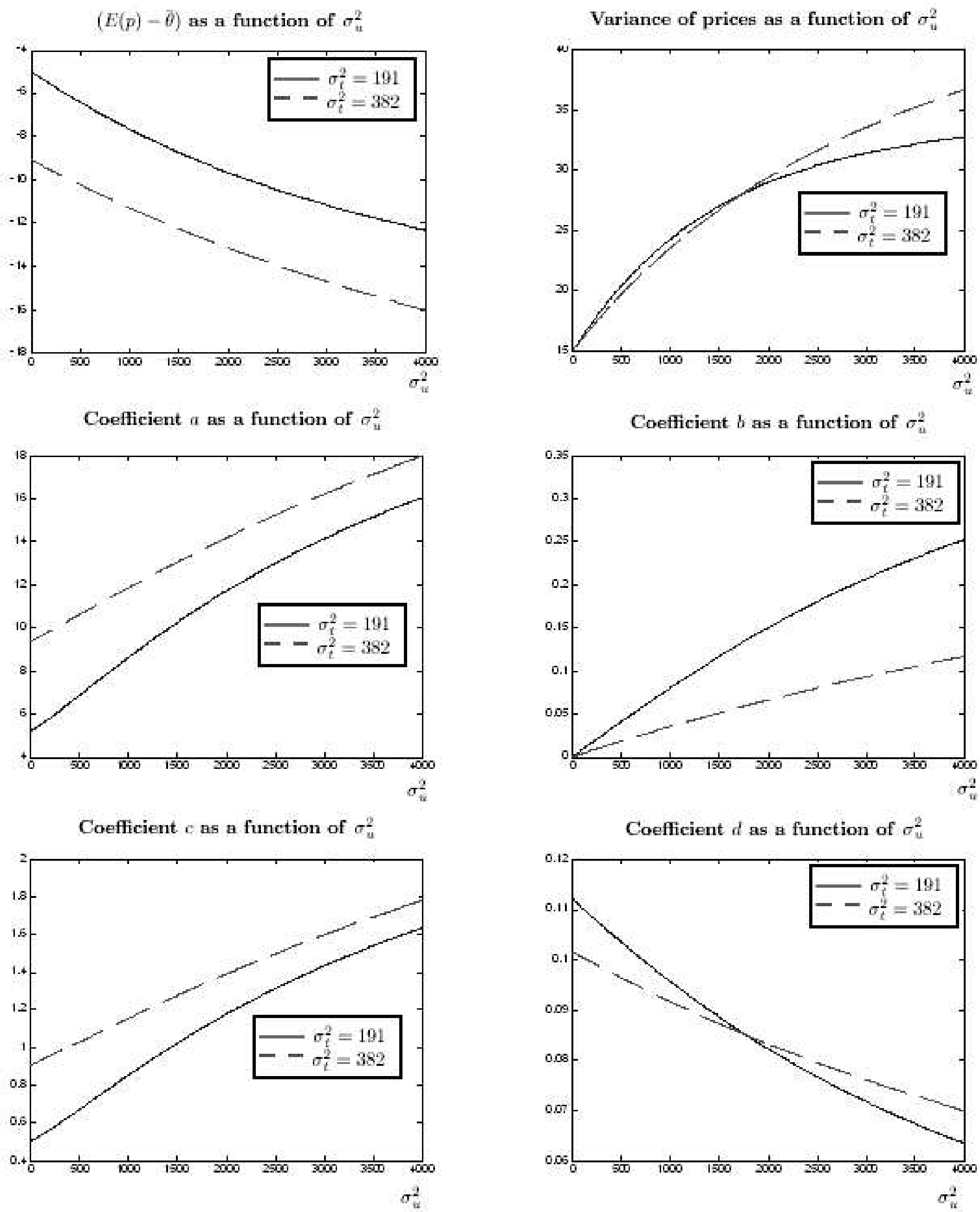
We obtain a fourth order equation in $\left(\frac{h}{b}\right)$ that always have only one positive real solution. Once $\left(\frac{h}{b}\right)$ is found, we can easily solve for all parameters.

In order to have additional information about the derived equilibrium and especially in order to make some form of testable predictions, we derive the equilibrium by using some numerical examples.

2.3 Some examples of equilibria

A first step to derive the numerical solutions to the equilibrium is to fix the values for some of the parameters. The fixed values are taken considering the environment of our experimental study. These are $Q = 80$, $n = 8$, $\sigma_\theta^2 = 221$, and $\overline{\theta} = 50$. Further we set $\sigma_\varepsilon^2 = 10$ and $r = 0.06$ so that the expected equilibrium prices and their variance remains relatively similar to the observed ones in the experiments. Given these parameters, we obtain the graph in Fig.2 .

Figure 2: Results of simulations for the theoretical equilibrium



The results illustrate how the parameters of the bidding function vary with the quality of the public signal measured by σ_μ^2. As we move from left to right, the quality of the signal deteriorates. Accordingly, the weight put on the public signal, d, decreases and the weight put on the private signal, b, increases. Furthermore, as the quality of the public signal decreases, the absolute value of the slope of the inverse demand curves increases. This is due to the fact that when the quality of the signal decreases, the adverse selection problem becomes more severe, a lower equilibrium price means more bad news, and bidders become more relucant to ask for much more units. These implications can be tested.

Table 1: Theoretical predictions

	If σ_μ^2 decreases	If σ_t^2decreases
$E\left(p^* - E\left[\theta\vert s\right]\right)$	increases	increases
$Var\left(p^* - E\left[\theta\vert s\right]\right)$	decreases	ambiguous
a	decreases	decreases
b	decreases	increases
c	decreases	decreases
d	increases	ambiguous

3 The experiment design

In order to compare the efficiency of regulating versus market-based transparency, we conduct a series of lab experiments. More precisely we ran a series of sealed-bid multi-unit auctions with common value. In these auctions, bidders submit for a risky asset A. Across the experiments, we vary the precision of information held by each agent prior to the auction as well as the availability of mechanisms allowing information transmission among participants. We setup three different treatments, each is divided into two different auctions that differ along the level of information available for participants. Hence, each treatment contains two auctions where (i) participants only have private signals about the risky asset A [henceforth, *Private Auctions*]; and (ii) all information held by all agents is made public [henceforth, *Public Auctions*]. Private and public information auctions serve as two extreme cases. Comparison between them permits identifying the impact of information on bidding behavior and the auction outcomes. The three treatments conducted present three different levels of transparency related to information transmission. The first treatment in the most opaque where we run simple auctions (*Simple auctions* hereafter). Auctions in the second treatment are preceded by a market based information aggregation mechanism, *i.e.* a market where agents can trade contracts related to asset A [henceforth, *IAM Auctions*]. By doing so, participants may infer some information about the future value of the asset A before the beginning of the auction. Finally, auctions in the third treatment are preceded by a pre-play communication round, where participants have the possibility (but not the obligation) to announce their private signals. These auctions will be called *Cheap-talk Auctions*.

In each of the three treatments we run, participants participate in 10 rounds, each round consists of one private information auction and one public information auction. Each treatment was run in different sessions. Throughout the session, participants win (and sometime lose) Experimental Monetary Units, EMUs. At the end of the sessions, EMU are transformed in dollars according to a fixed exchange rate announced in advance. The exchange rate has been calculated so that the average gain is around 15$can per hour (10$US per hour). A minimum amount of 8$can was given to each participant irrespective of his (her) performance in the game.

This experiment is aimed at comparing the market based information aggregation mechanism to the more obvious mechanism where subjects may share their information. Our goal is not to test the strategic behavior of agents when announcing signals but to study the effects of the new signal on the bidding behavior of subjects and to compare its informational contribution relatively to the IAM auctions.

3.1 The simple auctions treatment

We first ran six sessions with simple auctions. The auctioneer sells a fixed amount of a risky asset A whose value is θ. The value $\theta \in [25, 75]$ is set at the beginning of the round (drawn uniformly among all integer values between 25 and 75) and is not revealed to participants before the end of the round.

Prior to the so-called "private information auction", each participant observes a private signal about θ. This signal is a fixed number of balls (six or twelve) each may be red or blue. A ball will be red with probability $\theta\%$ (and blue with probability $(100 - \theta)\%$). As the number of red balls is the private information, each participant has partial information about θ. The number of balls distributed measure the precision of private signals about θ. For each round, precision of private signals may be either six or twelve balls with equal probability. Precision was always the same for all participants. Based on that information, participants were invited to submit their bids.

A bid from a participant was a set of four prices. Each had to submit the highest prices at which (s)he was ready to buy respectively 5, 15, 25 and 35 units of the asset A. The prices submitted had to be between 0 and 100. No other restriction were imposed on bids. A "private information auction" was immediately followed by a "public information auction". Without revealing the outcome of the first auction, we revealed to all participants the total number of red balls received by all participants. Given that new information, participants were invited to resubmit new bids. The electronic auctioneer then calculates prices and allocation rules in both cases as well as individual profits. As stated above, all units were sold at the same price, which is the highest market clearing price (uniform rationing is applied in case of ties). In order to limit the linkage between private and public information auctions outcomes, only one of the two auctions was used to calculat the participants' payoffs. Which auction was used to calculate gains was determined by a coin flip. Subjects were told these rules in advance.

In the first four sessions, we had 8 participants per auction, in the last two sessions we had 7 participants, for a total of 46 different subjects. In order, to adjust for the number of participants, the total number of units sold in the auction was set to ten times the number of participants.

3.2 The IAM Auctions treatment

We ran, with different subjects, 5 sessions of IAM auctions. The basic structure of the experiments is the same as before with the exception that prior to each pair of auctions, we ran a double-sided market created to act as an Information Aggregation Mechanism (IAM). Each participant receives 10 units each of two financial assets A and B. Each asset A is worth θ EMU while each asset B is worth $(100 - \theta)$ EMU. After receiving their private signals, participants were invited to trade their A and B contracts in a double-sided market. Note that if a participant keeps an equal number of assets A and B, he remains entirely protected against risk, but he can, if he believes it is advantageous, exchange contracts A for B contracts or *vice versa*.

Participants in the double-sided market can submit buy or sell orders for one unit of asset A. If one desires to purchase more than one unit, (s)he needs to issue more than one order. Further, as there is no *numéraire* in this market, all trades are executed in exchange for units of B. Hence, if one wishes to buy one unit of A at a price p, (s)he must give in exchange $\left(\frac{100-p}{p}\right)$units of B. The important principle to understand is that it will be advantageous to buy (sell) units of assets A at price p if and only if the true value of asset A is greater (less) than p.

The trading period lasts between 3 and 5 minutes. In order to encourage trading, after the first three minutes, trading period may stop before the end of the 5 minutes clock if in the last 30 seconds no new trade executed or no new order was submitted at a better price. In each session, two training rounds were run in order to make sure that the trading rules were understood and that subjects were able to use the exchange interface.

Once the double-sided exchange was closed, participants were invited to submit bids to purchase more units of asset A. The rest was identical to the previous treatment. In each round, we ran one auction immediately after the double-sided exchange, next we revealed all the available signals and ran another identical auction. As in the initial treatment, only the outcome of one of this two auctions were used to calculate the subject's payoff. In all cases, the EMU won or lost in the double-sided exchange were added or subtracted to the subject's account.

The number of participants in each session varied. In three cases, we began with 8 subjects; in two of those session we ended up with 7 subjects has one of the participants went bankrupt. In the other sessions, we started with 7 subjects; in one case we ended up with six participants and in the other with five.

3.3 The Cheap-talk auctions treatment

Finally, we run six sessions of cheap-talk auctions. In this treatment, the auctions were preceded by a round of pre-play communication where each subject, after seeing his private signal, was asked to announce his signal. He was not however compelled to be truthful. Then each agent observes the aggregate signal announced by agent as well as his private signal. Then bidding takes place exactly as for the simple auction treatment. Then, in the public Cheap-talk auctions, the aggregate signal for participants was announced and bidding took place. The number of subjects in each session was either 8 or 7 (8 for the 4 first sessions and 7 for sessions 5 and 6).

The experiments were conducted mid-September 2002 (for Simple and IAM auctions) and mid-march 2003 (for Cheap-talk auctions) in the LUB-C3E lab at the CIRANO (Montreal). We conducted a total of 17 sessions. Subjects were recruited from the student population of the Montreal region through the data base of the Bell Universitity Lab at the CIRANO. The experiments were computerized using the software *Z-Tree* developed at the University of Zurich (Fischbacher, 2002). Each subject participates only to one experimental session. A total of 130 subject participated in one of the three treatments. For all sessions, a presentation of the rules of the experiment as well as the information structure are made for all subjects using a powerpoint file. During the presentation, subjects were encouraged to ask clarifying questions. Presentations last on average 25 minutes for Simple and Cheap-talk auctions and 30 minutes for IAM auctions.[4]

In six of these sessions, we ran simple auctions. In the five others, each auction was preceded by the so-called "Information Aggregation Mechanism". Finally in the last 6 sessions, auctions were preceded by a pre-play communication round. In total, we ran 170 auctions with private information each followed by a public information auction. More precisely, we conducted 60 simple auctions, 50 IAM auctions and 60 cheap talk auctions. Throughout the experiment, the number of participants varied. All sessions began with either 8 or 7 participants. In some few cases, the number of participants decreased during the session because some participants went bankrupt and had to withdraw from the experiment. In total, we recorded 920 individual bids in simple auctions (460 private and 460 public), 920 individual bids in cheap-talk auctions (460 private and 460 public) and 704 individual bids in IAM auctions (352 IAM and 352 public).

4 Experiment Results and Empirical analysis

In this section, we analyze the data obtained from the experiments. We consider two different issues: (i) The impact of transparency on equilibrium prices and (ii) its impact on bidding behavior of agents.

[4]Powepoint files of presentations are available under request.

4.1 Impact of transparency on equilibrium prices

Transparency in our experiment is measured by the level of information available for subjects in different auctions. We consider two sources of public information: publicly disclosed information and information generated by an information aggregation mechanisms (cheap-talk or market-based). The theoretical prediction is that better public information should lead to prices that are closer to the accurate value of the asset, *i.e.* higher average equilibrium prices and lower variance.

For each observation, we calculate the expected value of θ given the aggregate information. Let denote this value p^*. [5] This price is the expected value of the assets given the distributed public information. We measure the performance of each auction as the difference between the selling price and the corresponding p^*. Table 2 presents summary statistics about the differences between auction prices and p^* for different treatments.

These summary statistics suggest some interesting patterns. For almost all treatments (except private cheap-talk auctions) differences are significantly negative suggesting that subjects are aware of the level of uncertainty on their bidding decisions but not significantly different from one another. Moreover, public information treatments exhibit lower variations of price errors than private information treatments thanks to the more precise information subjects may observe in these environments. In order to corroborate these observations, we conduct different statistical tests.[6]

[5] If m is the number of balls drawn and if l is the number of red balls among those, then p^* is given by:

$$\begin{aligned} p^* &= E\left[\theta|m,l\right] = \frac{\sum_{\theta=25}^{75} \theta \binom{m}{l} \left[\frac{\theta}{100}\right]^l \left[\frac{(100-\theta)}{100}\right]^{m-l} \frac{1}{51}}{\sum_{\theta=25}^{75} \binom{m}{l} \left[\frac{\theta}{100}\right]^l \left[\frac{(100-\theta)}{100}\right]^{m-l} \frac{1}{51}} \\ &= \frac{\sum_{\theta=25}^{75} \left[\theta\right]^{l+1} \left[(100-\theta)\right]^{m-l}}{\sum_{\theta=25}^{75} \left[\theta\right]^{l} \left[(100-\theta)\right]^{m-l}} \end{aligned}$$

[6] We present only results for parametric tests. Kolomogorov-Smirnov tests give results favouring normality of distributions for all series of observations. Equivalent non parametric tests give the same results in all cases.

Table 2: Summary statistics for pricing errors

	Simple auctions		IAM auctions		Cheap-talk auction	
	private	public	private	public	private	public
Mean	-4.43**	-3.77**	-2.92*	-3.50**	-0.82	-2.03**
Median	-3	-3	-2	-3	1.5	-2
Std Dev	9.70	6.06	9.09	5.57	10.45	4.86
N obs	60	60	50	50	60	60

Note: Price deviation is measured as the difference between the equilibrium price and the expected value of the asset conditional on the available information.
* significantly different from zero at 1% level, two-tailed t-test
** significantly different from zero at 5% level, two-tailed, t-test

First, we compare the average price deviations for all treatments. The statistical significance ($p-$value) for the Brown-Forsythe test is 0.154, suggesting that means are not statistically different. Then, we compare only private treatments as well as public information treatments. For both cases, thre is no statistical difference between price deviations ($p-$values for the Brown-Forsythe test are 0.188 and 0.131 respectively. Finally we carry out pairwise comparisons between all six treatments. When we compare public and private within the same treatment we use paired samples t-tests. For inter-treatments comparisons, independent samples t-tests are used. After adjusting for the hypothesis of equality of variances, we find that all average price deviations are not statistically different at the 5% level of significance.

Then we test the homogeneity of variances of price deviations among treatments by considering all treatments, all public treatments and all private treatments. For each test, the null hypothesis is that variances of price deviations are the same for the treatments we consider. We find that price deviations' variances are not different for public and private treatments whereas, they are statistically different when we consider all treatments ($p-$values for the Levene's test are 0.380, 0.679 and <.001, respectively). Table 3 contains the results of pairwise comparisons between variances of price deviations. The bold numbers correponds to the significative differences.

All these results allow us to claim the following:

Result 1a: *Price deviations (from the expected value of the asset) for private information treatments have similar distributions.*

TABLE 3: PAIRWISE COMPARISONS BETWEEN VARIANCES OF PRICE DEVIATIONS

	Simple auctions	IAM auctions		Cheap talk Auctions	
	public	private	public	private	public
Private Simple Auctions	**1.60**[a] (**0.00**)	1.07 (0.79)	**1.74** (**0.00**)	0.93 (0.56)	**1.99** (**0.00**)
Public Simple Auctions		**0.67** (**0.00**)	1.09 (0.99)	**0.58** (**0.00**)	1.28 (0.24)
Private IAM Auctions			**1.63**[a] (**0.00**)	0.87 (0.40)	**1.87** (**0.00**)
Public IAM Auctions				**0.53** (**0.00**)	1.15 (0.20)
Private Cheap talk Auctions					**2.15**[a] (**0.00**)

Price deviation is measured as the difference between the equilibrium price and the expected value of the asset conditional on the available information. For each couple of treatments the ratio of standard deviations is reported (rows/columns).
[a] is for paired samples (public versus private auctions within each treatment). In this case, p-values for t-tests on differences between absolute values of price deviations are between parentheses. .For all other comparisons between treatments where samples are independent, $p-$values for Levene's Test are between parentheses.

RESULT 1B: *Price deviations (from the expected value of the asset) for public information treatments have similar distributions.*

RESULT 1C: *Price deviations (from the expected value of the asset) for private and public information treatments are not different on average. However, variances of price deviations are significantly larger in private information treatments than in public information treatments.*

Overall, these results suggest that the level of information available for subjects is partially exploited by subjects and so partially reflected in prices.[7] Result 1B stipulates that public information in simple auctions lead to the same equilibrium outcome when compared to public IAM auctions and public Cheap-talk auctions. Moreover, when we compare private and public information treatments, we find that variances of price deviations decrease when subjects have access to more precise information. So, consistently with previous works dealing with market efficiency (for example Lundholm (1991)), we find that the availability of information for agents increases the probability of having prices closer to the expected value of the assets.

[7]In order to study whether these results are affected by the learning effect, we make the same analysis using only the last five auctions in each session. There is no significant change with respect to the first analysis. Results of this analysis are available upon request.

Table 4: Six versus twelve balls within each treatment

	Simple auctions		IAM auctions		Cheap talk Auctions	
	private	public	private	public	private	public
Mean	0.000	0.222	−4.24	**−3.24**	**6.70**	0.867
	(1.000)	(0.865)	(0.105)	(**0.065**)	(**0.018**)	(0.473)
Variations	−2.297	−0.889	2.32	**1.88**	**−4.767**	**−3.067**
	(0.132)	(0.392)	(0.141)	(**0.077**)	(**0.001**)	(**0.000**)

This table presents differences between average price deviations (in mean row) and differences of absolute values of price deviations used as measures of price deviation variation between six and twelve balls between treatments (twelve balls/six balls). For comparisons of means $p-$values for $t-$tests of paired samples are between brackets. For comparisons between variations we compare absolute values of price deviations. The $p-$values for t-tests on these differences are presented between brackets.

We now look at the impact of the quality of private information on the equilibrium price. In some auctions, subjects were given a signal based on the draw of six balls whereas in others the number of these balls is twelve. In this latter case the quality of each subject's signal is higher for both private and public information environments. The theoretical prediction is that as the quality of the private signal increases, measured by a decrease in σ_t^2, equilibrium prices should be closer to the expected value. The impact on the variance of equilibrium prices is ambiguous. In Table 4, we compare the six and twelve balls mean and variance of equilibrium prices, $E\left(p^* - E\left[\theta|s\right]\right)$ and $Var\left(p^* - E\left[\theta|s\right]\right)$, within each treatment. The bold numbers correspond to the significative statistics.

Note that distributions of price deviations are similar for six and twelve price deviations in both private and public simple auctions as well as private IAM auctions. This suggests that in all these cases, information precision does not affect the equilibrium price. For public IAM auctions, the higher information precision increases price deviations and decreases its variability. In private Cheap talk auction, price deviations are on average higher for six balls case though its variance is significantly lower. Finally, in public cheap-talk auctions, we find that variations of price deviations are significantly lower in the six balls case whereas, average price deviations are the same for both levels of information precision.

In summary, the quality of both the private and public signal does not seem to affect equilibrium price levels. Disclosing all available information seems, as expected, to lower the variance of equilibrium prices. However, the presence of an information aggregation mechanism does not seem to affect equilibrium price distribution. In order to study more deeply the impact of transparency, we need to examine its impact on bidding behavior. This is what is done in the next subsection.

4.2 Impact of transparency on bidding behavior

Through our experiments, we have collected 10,176 individual bids. We exploit this data to examine how bidding behavior varies across the various treatments. Each individual bid contains four maximum prices the subject is ready to pay in order to receive, respectively, up to 5, 15 , 25 and 35 units of the risky asset. In the theoretical model, we derive a demand function of the form:

$$p = a + bs_i + dS - cx - h\epsilon_i$$

where s_i is the private signal of the agent, S is the public signal available for agents, x is the quantity demanded, and finally ϵ_i represents the initial wealth of agent i. As presented in Figure 2, the theoretical model makes some predictions about how the parameters a, b, c and d vary with the quality of the private and public signal. The parameters a, b and c are decreasing in the quality of the public signal while d is increasing.

Using our experimental observations, one can estimate an aggregate inverse demand function in each treatment. We do not have the presumption of estimating a structural model as the assumption underlying the theoretical model do not correspond to the experiment framework from which the data was drawn from. However, we believe that the model provides qualitative insights that can be transposed to the data. Adjusting the theoretical demand function to our environment, we consider the following model:

$$p_i = \beta_0 + \beta_1 E(\theta|s_i) + \beta_2 x + \beta_3 E(\theta|S) + \beta_4 E(\theta|S_2) + \beta_4 \ln(W) + \beta_4 NbPart + \varepsilon_i \qquad (24)$$

where $E(\theta|s_i)$ is the best estimate of the risky asset value that each subject may infer given his private signal while $E(\theta|S)$ and $E(\theta|S_2)$ denote the best estimate given some public signal. In public IAM and cheap-talk auctions we consider two public signals, the announced aggregate signal ($E(\theta|S)$) and the public signal inferred from the pre-auction communication game

$(E(\theta|S_2))$. In IAM auctions, this presents the information subjects infer from the outcome of the double-sided market. We use the average trading price in these markets as a proxy for this signal. This signal is also used as the public signal in private IAM auctions. In cheap-talk auctions, the public signal is the expected value of the asset given the aggregate signal announced by subjects. This is also the public signal we consider in private cheap-talk auctions. Moreover, we consider two variables that may affect the trading strategies of subjects. The first variable is the level of their wealth before submitting orders. Because of the structure of payments for subjects, we argue that their strategies will be positively affected by their wealth. The second variable is the number of participants in the auction. This variable measures the level of competition in the game as well as the level of informativeness of public signals.

Note that in theory (under the assumption of common knowledge and rationality), public auctions should be invariant to whether they are preceded or not by an IAM or a cheap-talk mechanism, since in principle, the IAM or cheap talk does not add any relevant information that participants do not already have when public signals are announced. In particular, the parameter β_4 should be zero when the full public information is disclosed.

The results of regressions for grouping data are presented in Table 5. The significative coefficients are in bold.

Result 2a: *Not surprisingly, the level of wealth significantly affect positively the inverse demand functions of subjects in all treatments.*

Result 2b: *The number of competitors affects negatively trading strategies of agents in both IAM and cheap-talk auctions. However, in simple auctions, the number of participants affects positively the price subjects are ready to pay for a given quantity.*

Result 2c: *The bidding behavior differs between treatment, when all information is publicly diclosed. In regression 4, bidders rely on the publicly disclosed information but also on their private signal. In both regressions 5 and 6, bidders rely on the publicly disclosed information and do not use their private signals. Moreover, in regression (5), subjects also use the market-based public signal Hence, the presence of an information aggregation mechanism affects bidding behavior. This is true not only when the information aggregation mechanism provides the only*

Table 5: Aggregate inverse demand functions for different treatments (p-values are between parentheses)

	Simple auctions		IAM auctions		Cheap-talk auctions	
	Private	Public	Private	Public	Private	Public
	(1)	(4)	(2)	(5)	(3)	(6)
Intercept	**−51.330**	**−34.586**	**−33.450**	**−30.266**	**−13.383**	**−19.040**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.031)**	**(0.001)**
quantity (x)	**−0.315**	**−0.280**	**−0.176**	**−0.163**	**−0.418**	**−0.365**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Exp Priv	**0.758**	**0.218**	**0.474**	0.034	**0.494**	0.034
($E(\theta\|s_i)$)	**(0.000)**	**(0.000)**	**(0.000)**	(0.459)	**(0.000)**	(0.378)
Exp Pub	-	**0.411**	-	**0.501**	-	**0.627**
($E(\theta\|S)$)		**(0.000)**		**(0.000)**		**(0.000)**
Exp Pub2	-	-	**0.349**	**0.186**	**0.216**	0.027
($E(\theta\|S_2)$)			**(0.000)**	**(0.006)**	**(0.000)**	(0.396)
$Ln(W)$	**6.314**	**4.652**	**6.510**	**6.507**	**5.906**	**5.882**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
$NbPart$	**1.940**	**2.053**	**−0.879**	−0.639	**−1.584**	−0.625
	(0.007)	**(0.008)**	**(0.016)**	(0.080)	**(0.011)**	(0.292)
Adj R^2	0.289	0.240	0.270	0.332	0.287	0.447
Sig. ($p-$value)	0.000	0.000	0.000	0.000	0.000	0.000
N	1840	1840	1408	1408	1840	1840

source of public signal, but also when the public information is fully disclosed.

Result 2c suggests that subjects give higher importance to the market based signal. But, this also shows that subjects deviate from the theoretical model since they "irrationally" use the market-based signal even when they have access to a more precise signal.

Next, the inverse demand functions in private and public auctions within each treatment are compared using the following model:

$$p_i = \alpha_0 + \alpha_1 E(\theta|s_i) + \alpha_2 x + \alpha_3 E(\theta|S_2) + \alpha_4 \mathbb{P} + \alpha_5 x\mathbb{P} + \alpha_6 E(\theta|s_i)\mathbb{P} + \alpha_7 E(\theta|S)\mathbb{P} + \alpha_8 E(\theta|S_2)\mathbb{P} + \alpha_9 \ln(W) + \alpha_{10} NbPart + \varepsilon_i \quad (25a)$$

where $\mathbb{P}$ is a dummy variable equal to 1 if we are in a public information treatment. The sign and the statistical significance of α_4, α_5, α_6 and α_7 are examined. The results of these regressions are displayed in Table 6. The relevant and significative parameters are in bold.

Table 6: Comparison of inverse demand functions in private and public auctions within different treatments (p-values are between parentheses)

	Simple auctions	IAM auctions	Cheap-talk auctions
Intercept	−45.364 (0.000)	−34.491 (0.000)	−17.200 (0.000)
Quantity (x)	−0.315 (0.000)	−0.176 (0.000)	−0.418 (0.000)
$E(\theta \mid s_i)$	0.759 (0.000)	0.475 (0.000)	0.494 (0.000)
$E(\theta \mid S_2)$	–	**0.352** (**0.000**)	**0.221** (**0.000**)
Public $\mathbb{P}$	6.839 (0.007)	5.256 (0.221)	1.981 (0.473)
$x * \mathbb{P}$	0.035 (0.414)	0.014 (0.722)	0.053 (0.117)
$E(\theta \mid s_i) * \mathbb{P}$	**−0.541** (**0.000**)	**−0.441** (**0.000**)	**−0.460** (**0.000**)
$E(\theta \mid S) * \mathbb{P}$	**0.410** (**0.000**)	**0.148** (**0.043**)	**0.407** (**0.000**)
$E(\theta \mid S_2) * \mathbb{P}$	–	**0.183** (**0.007**)	0.022 (0.494)
$ln(W)$	5.483 (0.000)	6.508 (0.000)	5.894 (0.000)
$NbPart$	1.994 (0.000)	−0.758 (0.003)	−1.105 (0.010)
Adj R^2	0.264	0.302	0.373
sig. (p−value)	0.000	0.000	0.000
N	3680	2816	3680

$\mathbb{P}$ is a dummy variable equal to 1 in public information auctions and 0 in private information auctions

In all cases, the higher precision of public signals (so moving from a private to a public information environment) leads to a reduction of both private signals and quantities (in absolute values) coefficients, and to an increase of the sensibility to public signals. This is consistent with the prediction that parameter b is decreasing while parameter d is increasing with the quality of the public signal. Finally, as suggested by the numerical simulations, the absolute value of the slope of the demand functions decreases with the precision of the public information signal, however these differences are not significative.

RESULT 3A: *In each treatment, bidding behavior by subjects are different when moving from a private to a public information environment.*

RESULT 3B: *In each treatment, the observed bidding behavior confirms the theoretical predictions that the sensitivity of inverse demand functions is decreasing with respect to private signals and quantities and increasing with respect to public signals.*

Next, the inverse demand functions across each treatment are compared using the following model:

$$\begin{aligned} p_i &= \beta_0 + \beta_1 E(\theta|s_i) + \beta_2 x + \beta_3 E(\theta|S) + \beta_4 E(\theta|S_1) + \beta_5 \mathbb{I} + \beta_6 x \mathbb{I} + \beta_7 E(\theta|s_i)\,\mathbb{I} + \\ & \quad \beta_8 E(\theta|S)\,\mathbb{I} + \beta_9 \ln(W) + \beta_{10} NbPart + \varepsilon_i. \end{aligned} \tag{26}$$

This model will be used to compare the impact of information aggregation mechanisms. We compare simple auctions with both IAM auctions and cheap-talk auctions. The variable $\mathbb{I}$ is a dummy variable equal to one when subjects have access to an information gathering mechanism and zero otherwise. Then, we compare also IAM auctions and Cheap talk auctions. In this case, the variable $\mathbb{I}$ is equal to 1 when subjects participate in IAM auctions and zero when they participate in cheap-talk auctions. Table 7 contains the results of this analysis.

The objective, here, is to explore the impact of pre-auction Information Aggregation Mechanism. In all cases, the higher quality of public signals leads to a reduction of both private signals and quantities (in absolute values) coefficients, and to an increase of the sensibility to public signals. This is consistent with the prediction that parameter b is decreasing while parameter d is increasing with the quality of the public signal. Also, as suggested by the numerical simulations, the absolute value of the slope of the demand functions decreases with the precision of the public information signal, however these differences are not significative.

RESULT 4A: *In private information environments, the inverse demand finction estimates are consistent with the theoretical predictions and the assumption that the market based information aggregation mechanism conveys valuable public information, and more so than cheap talk based mechanism.*

Table 7: Comparison of inverse demand functions in private auctions for different treatments (p-values are between parentheses)

	Simple Versus IAM	Simple versus Cheap-talk	Cheap-talk versus IAM
Intercept	−35.667 (0.000)	−33.804 (0.000)	−19.486 (0.000)
quantity (x)	−0.315 (0.000)	−0.315 (0.000)	−0.418 (0.000)
Exp Priv $E(\theta\|s_i)$	0.745 (0.000)	0.748 (0.000)	0.495 (0.000)
Exp Pub $E(\theta\|S_2)$	–	–	0.221 (0.000)
$\mathbb{I}$	−3.940 (0.294)	6.882 (0.011)	−10.154 (0.005)
$x * \mathbb{I}$	**0.139** **(0.001)**	−0.104 (0.006)	**0.242** **(0.000)**
$E(\theta\|s_i) * \mathbb{I}$	**−0.268** **(0.000)**	**−0.255** **(0.000)**	**−0.023** **(0.604)**
$E(\theta\|S_2) * \mathbb{I}$	**0.370** **(0.000)**	**0.234** **(0.000)**	**0.122** **(0.090)**
$ln(W)$	6.397 (0.000)	5.784 (0.000)	6.234 (0.000)
$NbPart$	−0.083 (0.813)	0.183 (0.697)	−1.104 (0.000)
Adj R^2	0.288	0.286	0.287
sig. ($p-$value)	0.000	0.000	0.000
N	3248	3680	3248

$\mathbb{I}$ is a dummy variable equal to 1 for IAM auctions and 0 otherwise except for comparison between simple auctions and cheap talk auctions where $\mathbb{I}$ is equal to 1 for cheap talk auctions.

For private information environments, notice that inverse demand functions are steeper (with respect to quantities) for cheap talk auctions than for simple auctions. This contradicts the theoretical prediction. Indeed, since cheap talk auctions are supposed to have a higher level of information availability (by allowing subjects to observe the aggregate signal), we expect the inverse demand function to be steeper the worse is the quality of the public signal. So, it seems that subjects do not rely on the signals sent by their rivals in the pre-play communication round. It seems even that this round makes them more puzzled since they behave as if they were in a worse informational position than in simple auctions.

Result 4b: *In private information environments, the inverse demand finction estimates are not consistent with the theoretical predictions or the assumption that the cheap talk based information aggregation mechanism conveys valuable public information.*

We turn now to see the effect of increasing the private signals' quality on trading behavior. The following model is aimed at comparing, for each treatment, demand functions under two levels of information precision (6 balls and 12 balls auctions).

$$\begin{aligned} p_i &= \beta_0 + \beta_1 E\left(\theta|s_i\right) + \beta_2 x + \beta_3 E\left(\theta|S\right) + \beta_4 E\left(\theta|S_2\right) + \beta_5 \mathbb{B} + \beta_6 x\mathbb{B} + \beta_7 E\left(\theta|s_i\right)\mathbb{B} + \beta_8 E\left(\theta|S\right)\mathbb{B} + \\ &\quad \beta_9 E\left(\theta|S_2\right)\mathbb{B} + \beta_{10}\ln(W) + \beta_{11} NbPart + \varepsilon_i \end{aligned}$$

with $\mathbb{B}$ is a dummy variable equal to one when signals are based on twelve balls and equal to zero for signals based on six balls. The results of this analysis are summarized in Table 8 in Appendix B. It seems that the higher precision of signals does not affect subjects' behavior since almost all coefficients are not statistically significant.

Result 5A: *Increase in the quality of the private signal (moving from 6 to 12 balls) did not had the expected effect.*

As a final step in this analysis, we test the robustness of our results with respect to learning effects. We introduce a dummy variable equal to one for the last five auctions in each session and zero for the five first auctions. Overall, there is no learning effect in our experiment. Indeed, neither the signs nor the relative values and statistical significance of all coefficients vary when we consider the last five auctions in each treatment. See Table 9 in Appendix B.

5 Application to IPOs

The fundamental problem in IPOs is finding out the new stock's value. Most companies conducting an IPO are very young, situated in growth industries, and working with innovative technologies and so oftentimes the benchmark cases are missing (Kim and Ritter 1999). This exacerbates information asymmetries between different participants in the IPO. Such information asymmetry is largely used to explain the underpricing phenomenon observed in IPOs (Rock, 1986; Benveniste and Spindt, 1989). This issue was largely studied in financial empirical literature. For example, Cornelli and Goldreich (2001) study allocations and strategic bidding (more precisely strategic announcement of indications of interest by investors) in the bookbuilding procedure.[8] They find that both the seller and buyers, through their actions, do consider effects of information asymmetries.

Our experimental design may be seen as a comparison of different IPO procedures where their performances are measured by their relative ability to lessen information asymmetry. These procedures are simple auctions, auctions preceded by a market based IAM and auctions preceded by a communication round. Note that the way bookbuilding is conducted is similar to our third procedure since underwriters collect information from investors by asking them to submit non binding indications of interest.[9]

In this work, our experimental results allow us to conclude the dominance of market based IAM in their role of mitigating adverse selection problems. This suggests that such mechanisms may be useful to lessen information asymmetry and so to reduce underpricing. The question that remains is: How should we implement this mechanism?

Such information aggregation mechanisms do exist in several primary markets. In US treasury markets, when-issued markets operate before the issuance of treasury securities. When-issued market is a forward market where future contracts on the securities to be issued are traded. Nyborg and Sundaresan (1996) study empirically the role of these markets in the process of selling treasuries. They argue that the when-issued markets play their role of aggregation of information that is relevant in the price discovery process of new treasury securities. An equivalent when-issued market, where future contracts are traded, exists for IPOs of shares in many European countries. In general, these markets operate concurrently with a bookbuild-

[8] Bookbuilding is the IPO procedure used in the US financial markets. It is also largely used around the world (see Sherman 2000).

[9] Cornelli and Goldreich (2001) report that institutional investors adjust the non binding indications of interest they announce to underwriters. This suggests that investors may try to affect the price determination process through their non binding announcements.

ing process. Aussenegg et al. (2003) examine the pricing process in the German IPO market featuring such coexistence of bookbuilding and when-issued trading. They find that while new-issued trading allows the revelation of relevant information, it cannot supplant bookbuilding as a source of information. Moreover, they report that underwriters begin the issuance process by gathering information through the bookbuilding (so by collecting information from investors). This information is then publicly displayed through price ranges. Afterward when-issued trading commences once these ranges are posted. This trading will help issuers to situate the IPO price within ranges. Henceforth, it seems that the information-gathering role of when-issued trading can be effective only if it is used concurrently with another direct mechanism aimed at alleviating the adverse selection risk. One major critique addressed to bookbuilding is its high cost for firms.[10] Obviously when-issued markets as designed in the German primary stock market do not overcome this drawback.

There are also two critics that may be addressed to when-issued markets. First, as argued in Aussenegg et al. (2003) and Pichler and Stomper (2004), when-issued markets suffer from viability problem. Indeed, because of the information asymmetry, when-issued markets may fail to open (or even have repetitive breakdowns) unless they are preceded by a direct mechanism permitting the alleviation of adverse selection problem. The second argument is related to the weakness of these markets to avoid transactions aimed at manipulating pricing in the IPO. In fact, heavy short selling of forward contracts may cause a downward revision of IPO prices even though information about the stock's value is not so bad. This argument is the reason behind restriction of when-issued trading in the US primary stock markets.[11]

In order to avoid the viability problem of when-issued trading of forward contracts, we argue that trading should have an optional feature. This will encourage investors to enter this market by having the possibility of avoiding the risk inherent to new stocks. Our experiment is designed in this spirit. Indeed, agents can always hedge their risky positions by balancing their portfolios

[10] See Chen and Ritter (2000). The high cost of bookbuilding procedure was one of the announced motivations for choosing an modified Duch auction IPO procedure for Google, Inc.

[11] Paragraph II.F of the Securities Exchange Act Release No. 38067 (December 20, 1996) on Regulation M, it is clearly stated that: "Such short sales could result in lower offering price and reduce an issuer's proceeds." (see the SEC's web site at http//www.sec.gov/rules/final/34-38067.txt)

(containing shares A and B) to have “riskless” positions. Note that option contracts may be a good alternative to forward contracts since options have, by definition, the optional feature desired to enhance viability of when-issued markets. However, option contracts will be more inclined to short sales critique that forward contracts.

We suggest that an alternative that may enhance viability and lessen the short sales problem through a differently structured market is the issuance of convertible bonds before the IPO date. We argue that convertibility option will enhance viability and, a suitably organized market for convertibles, will mitigate the impact of short selling manipulations. Our experiment is designed (A and B contracts) with the idea of using convertible bonds markets as an information aggregation mechanism. Since Convertibility option value depends on the stock's value, the issuance of convertibles before the IPO allows the firm to make possible the transmission of information between participates, and consequently alleviating the adverse selection risk. Our result favors this argument since we prove that information aggregation mechanisms mitigate adverse selection problem, and consequently, permit lower underpricing of new shares.

Last and not least, though the issuance of convertible bonds may contain some underpricing related to the convertibility option; the nominal value of this issue may be sufficiently low, so that this underpricing cannot offset the potential gain that may be realized through a more adequate pricing in the IPO caused by a lower adverse selection risk.

6 Conclusion

In this paper, we examine the impact of public information on equilibrium behavior and prices in common value multi-unit auctions. We begin by providing a closed-form equilbrium of a theoretical model. Under the assumption of the model, there exists an equilibrium where participants submit linear decreasing downward sloping demand curves. The parmeters of the demand function, including the slope of the demand curve with respect to quantity, will depend on the degree of risk aversion and the quality of the information available to the agent prior to the auction. Hence, the behaviour of the subjects in the multi-unit common value provides an indication of their appreciation of the information they have acquired prior to the auction. We believe that this offers a mean to measure indirectly the perceived quality of the signals generated from different Information Aggregation Mechanism.

The model has been tested on experimental data. Despite the fact that subjects were inexperienced and could not possibly figure out the optimal bidding strategy, the bidding pattern did vary with superior public information as predicted by the theoretical model. On the basis of this study, we found that the market-based information aggreation mechanism does provide useful information to the bidders, much more so then cheap-talk pre-auction communication. We believe that a market-based IAM could be used prior to the introduction of new financial assets in order to generate useful public information and reduce adverse selection. This mechanism may be implemented through a when-issued trading of convertible bonds.

Appendix A

Proof of Lemma 2. Recall that we have:

$$p = \left[-\frac{c}{(n-1)}(Q-x)+a+y\right] \text{ and } \tag{27}$$

$$E[\theta|Y,S,s_i] = \left(\frac{k_0}{k}\right)\bar{\theta}+\left(\frac{k_1}{k}\right)\left(\frac{y}{b}\right)+\left(\frac{k_2}{k}\right)\frac{(S-s_i)}{(n-1)}+\left(\frac{k_3}{k}\right)s_i \tag{28}$$

Hence, we can rewrite the first-order condition in (16) in order to find a relationship between x, a demand quantity, and, p, the equilibrium price which should not depend on y. Since $Var[\theta|Y,S,s_i] = \sigma_t^2 k_3$, we obtain the following relationship:

$$\begin{aligned} 0 &= \left[\left(\frac{k_0}{k}\right)\bar{\theta}+\left(\frac{k_2}{k}\right)\frac{(S-s_i)}{(n-1)}+\left(\frac{k_3}{k}\right)s_i+\left(\frac{k_1}{k}\right)\left(\frac{p+\frac{c}{(n-1)}(Q-x)-a-dS}{b}\right)\right] \\ &\quad -[p]-\left(\frac{c}{(n-1)}+r\sigma_t^2 k_3\right)(x+\epsilon_i) \end{aligned} \tag{29}$$

Isolating p, we obtain the following inverse demand function:

$$\begin{aligned} p &= \left(\frac{\left[bk_0\bar{\theta}+\frac{k_1 c}{(n-1)}Q-k_1 a\right]}{[bk-k_1]}\right)+\left(\frac{[b(n-1)k_3-bk_2]}{(n-1)[bk-k_1]}\right)s_i+\left(\frac{[bk_2-(n-1)dk_1]}{(n-1)[kb-k_1]}\right)S \\ &\quad -\left(\frac{((kb+k_1)c+(n-1)kbr\sigma_t^2 k_3)}{(n-1)[kb-k_1]}\right)x-\left(\frac{kb\left(c+(n-1)r\sigma_t^2 k_3\right)}{(n-1)[kb-k_1]}\right)\epsilon_i \end{aligned} \tag{30}$$

where by assumption

$$p = a+bs_i+dS-cx-h\epsilon_i \tag{31}$$

By matching the arguments of the two above equations and simplifying, we obtain the results of Proposition 1.

Note that the ratio $\left(\frac{h}{b}\right)$ enters into the definition of k_1 and k_2 where:

$$\left(\frac{h}{b}\right) = \left(\frac{k_3}{k_3-\frac{k_2}{(n-1)}}\right)\left(\frac{(n-1)k_3-k_2-k_1}{(n-2)k_3-\frac{(n-2)k_2}{(n-1)}-2k_1}\right)r\sigma_t^2 \tag{32}$$

One can verify that

$$\left[(n-2)k_3-\frac{(n-2)k_2}{(n-1)}-2k_1\right] > 0 \text{ if and only if } \left(\frac{h}{b}\right)^2 > \frac{n\sigma_t^2}{(n-2)\sigma_\varepsilon^2}$$

So as $\left(\frac{h}{b}\right)^2 \to \frac{n\sigma_t^2}{(n-2)\sigma_\varepsilon^2}$, the right-hand of (32) converges to infinity and is bigger than the left-side. Conversely, when $\left(\frac{h}{b}\right) \to \infty$, the left-side is finite and convergences to $\left(\frac{[\sigma_t^2(n-1)+\sigma_\mu^2]}{\sigma_\mu^2}\right)\frac{r\sigma_t^2}{(n-2)}$, and the right-hand of (32) converges to infinity and is bigger than the left-side.

By continuing, there exists a value $\left(\frac{h}{b}\right) > \sqrt{\frac{n\sigma_t^2}{(n-2)\sigma_\varepsilon^2}}$, that satisfies (32). For such a value, we have $\left[(n-2)k_3 - \frac{(n-2)k_2}{(n-1)} - 2k_1\right] > 0$. Hence, all parameters a, b, c, d and h are strictly positive. Further, since $c > 0$, note that the second-order condition in (17) is satisfied the above indeed forms an optimal response to other's strategies. ■

Appendix B

Table 8: Comparison of inverse demand functions in six balls and twelve balls auctions

for different treatments (p-values are between parentheses)

	Simple auctions		IAM auctions		Cheap-talk auctions	
	Private	Public	Private	Public	Private	Public
Intercept	-56.590 (0.003)	-37.298 (0.000)	-38.451 (0.000)	-30.467 (0.000)	-19.461 (0.005)	-24.129 (0.001)
quantity (x)	-0.266 (0.000)	-0.230 (0.000)	-0.162 (0.000)	-0.151 (0.000)	-0.383 (0.000)	-0.318 (0.000)
Exp Priv ($E(\theta\|s_i)$)	0.927 (0.000)	0.256 (0.001)	0.464 (0.000)	0.008 (0.902)	0.520 (0.000)	0.120 (0.040)
Exp Pub ($E(\theta\|S)$)	-	0.493 (0.000)	0.466 (0.000)	0.490 (0.000)	0.228 (0.000)	0.592 (0.000)
Exp Pub2 ($E(\theta\|S_2)$)	-	-	-	0.241 (0.009)	-	0.010 (0.852)
$\mathbb{B}$	13.297 (0.000)	9.205 (0.016)	10.645 (0.085)	2.137 (0.737)	9.587 (0.026)	8.450 (0.041)
$x * \mathbb{B}$	-0.090 (0.121)	-0.091 (0.140)	-0.027 (0.614)	-0.022 (0.686)	-0.063 (0.202)	-0.084 (0.073)
$E(\theta\|s_i) * \mathbb{B}$	-0.262 (0.000)	-0.025 (0.805)	0.030 (0.686)	0.041 (0.655)	-0.083 (0.192)	-0.123 (0.116)
$E(\theta\|S) * \mathbb{B}$	–	-0.161 (0.028)	-0.216 (0.094)	0.035 (0.647)	-0.047 (0.495)	0.015 (0.841)
$E(\theta\|S_2) * \mathbb{B}$	–	–	–	-0.067 (0.628)	–	0.005 (0.939)
$Ln(W)$	5.905 (0.000)	4.260 (0.000)	6.524 (0.000)	6.496 (0.000)	5.891 (0.000)	5.802 (0.000)
$NbPart$	1.868 (0.009)	1.974 (0.010)	-1.055 (0.005)	-0.911 (0.015)	-1.250 (0.046)	-0.366 (0.540)
Adj R^2	0.297	0.247	0.271	0.336	0.294	0.451
Sig. ($p-$value)	0.000	0.000	0.000	0.000	0.000	0.000
N	1840	1840	1408	1408	1840	1840

$\mathbb{B}$ is a dummy variable equal to 1 for twelve balls auctions and 0 for six balls auctions

Table 9: Effect of learning on the inverse demand function

	Simple auctions		IAM auctions		Cheap-talk auctions	
	Private	Public	Private	Public	Private	Public
Intercept	−111.748 (0.000)	−88.827 (0.000)	−10.870 (0.214)	3.688 (0.670)	15.902 (0.218)	−13.709 (0.246)
quantity (x)	−0.357 (0.000)	−0.301 (0.000)	−0.168 (0.000)	−0.141 (0.000)	−0.424 (0.000)	−0.372 (0.000)
Exp Priv ($E(\theta\|s_i)$)	0.740 (0.000)	0.337 (0.001)	0.389 (0.000)	−0.008 (0.896)	0.471 (0.000)	−0.007 (0.894)
Exp Pub ($E(\theta\|S)$)	-	0.310 (0.000)	0.419 (0.000)	0.455 (0.000)	0.140 (0.014)	0.634 (0.000)
Exp Pub2 ($E(\theta\|S_2)$)	-	-	-	0.285 (0.001)	-	0.071 (0.189)
$Ln(W)$	12.339 (0.000)	9.716 (0.000)	5.207 (0.000)	3.521 (0.000)	4.080 (0.012)	6.157 (0.000)
$NbPart$	4.926 (0.000)	4.727 (0.000)	−2.508 (0.000)	−2.580 (0.000)	−3.237 (0.000)	−1.636 (0.054)
$\mathbb{L}$	89.926 (0.000)	83.320 (0.000)	−27.001 (0.024)	−41.859 (0.000)	−43.127 (0.004)	−12.740 (0.372)
$x * \mathbb{L}$	0.084 (0.142)	0.042 (0.491)	−0.017 (0.749)	−0.046 (0.387)	0.012 (0.800)	0.015 (0.751)
$E(\theta\|s_i) * \mathbb{L}$	0.035 (0.587)	−0.242 (0.016)	0.132 (0.067)	0.066 (0.464)	0.043 (0.418)	0.074 (0.334)
$E(\theta\|S) * \mathbb{L}$	–	0.227 (0.002)	−0.128 (0.361)	0.052 (0.491)	0.105 (0.139)	−0.023 (0.685)
$E(\theta\|S_2) * \mathbb{L}$	–	–	–	−0.197 (0.183)	–	−0.075 (0.267)
$Ln(W) * \mathbb{L}$	−7.853 (0.000)	−6.802 (0.001)	2.023 (0.050)	4.357 (0.000)	1.838 (0.301)	−0.471 (0.780)
$NbPart * \mathbb{L}$	−5.476 (0.000)	−4.991 (0.001)	1.469 (0.072)	2.173 (0.007)	3.113 (0.014)	2.216 (0.064)
Adj R^2	0.299	0.251	0.284	0.347	0.288	0.447
Sig. ($p-$value)	0.000	0.000	0.000	0.000	0.000	0.000
N	1840	1840	1408	1408	1840	1840

For each treatment the following model is used:

$p_i = \beta_0 + \beta_1 E(\theta|s_i) + \beta_2 x + \beta_3 E(\theta|S) + \beta_4 E(\theta|S_2) + \beta_5 \ln(W) + \beta_6 NbPart + \beta_7 \mathbb{L} + \beta_8 x\mathbb{L} + \beta_9 E(\theta|s_i)\mathbb{L} + \beta_{10} E(\theta|S)\mathbb{L} + \beta_{11} E(\theta|S_2)\mathbb{L} + \beta_{12} \ln(W)\mathbb{L} + \beta_{13} NbPart\mathbb{L} + \varepsilon_i$

where $\mathbb{L}$ is a dummy variable equal to one for the last five auctions in each session and zero for the five first auctions

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