Market for information and identity disclosure in an experimental automated market

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Abstract

This paper analyzes the effect of pre-trade transparency on market quality in an experimental automated continuous auction market preceded by a market for information. We find that disclosure of traders' identities reduces the incentive to acquire information, liquidity and volatility. The results are consistent with a model of price formation according to which when the number of traders buying information is endogenous, transparency reduces liquidity.

JEL classification codes: D84, G14.

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1 Introduction

This paper deals with pre-trade transparency, i.e. the dissemination of information to participants before transactions are concluded. In the debate on market design, this issue is a highly controversial one.

Here we build an experiment to study the effects of pre-trade transparency on market quality[1]. Specifically, we inquire into how the disclosure of traders' identities influences the quality of an automated double auction financial market. Increasingly, markets around the world are automated (Domowitz and Steil, 1999), and in most of these, traders' personal markers are not displayed. This is why we choose to design our experimental market as an electronic open book, analogous, for example, to the system in use at the Paris Bourse, the Milan Stock Exchange, the ECNs, the EBS in the foreign exchange market and MTS Global markets[2]. We reproduce both an anonymous and a transparent market, the latter displaying traders' personal markers. Our main finding is that transparency lowers the number of participants who decide to buy information, thus reducing liquidity and volatility.

[1]This paper is not concerned with post-trade transparency, i.e. with disclosure rules for completed trades.

[2]MTS Global consists of the European domestic markets for government bonds and EuroMTS, the European benchmark bond market.

Existing theoretical and empirical studies in this field give contradictory results. Several theoretical works emphasize the positive effect of transparency concerning liquidity traders' demand on adverse selection costs (for example Pagano and Röell, 1996 and Röell, 1990). Forster and George (1992) examine the effects of disclosing the sign and magnitude of liquidity traders' orders and find that transaction costs vary with the type of information and the degree of competition among insiders. Admati and Pfleiderer (1991) develop a model to analyze the effects of preannouncement by liquidity motivated traders of their intention to trade, finding that this reduces their trading costs but has ambiguous effects on those of other traders. Madhavan (1996) shows that in a market with strategic informed liquidity providers, information about liquidity traders' demand improves informational efficiency and has an ambiguous effect on liquidity.

In the real world, there have been very few examples of changes in the degree of transparency, so the empirical evidence on the effects of pre-trade transparency on market quality is quite limited. Harris and Schultz (1997) find that market makers lose on trades executed in the anonymous SOES system and accordingly they widen the bid-ask spread. Garfinkel and Nimalendran (1998) show that on insider trading days the increase in the bid-ask spread is greater on NYSE than on NASDAQ, attributing this to the former's greater transparency. Madhavan, Porter and Weaver (1999) examine the natural experiment by the Toronto Stock Exchange when it publicly disseminated the limit order book on both the traditional floor and its automated trading system and find that after the change execution costs and volatility increased. Theissen (2000) studies the non-anonymous floor-based trading system of the Frankfurt Stock Exchange; he shows that specialists grant price improvements to traders thought to be uninformed and concludes that transparency enhances liquidity since it facilitates market markers' ability to offer price discounts.

Experimental economics can significantly enrich this debate. Field data studies cannot control for the number of market participants, their trading profits and investment strategies, nor do allow one to control for changes in market structure, which are normally associated with changes in pre-trade transparency. The experimental approach to investigating transparency has been taken by a number of works. Banks (1985) extends Plott and Sunder's oral double auction experiment to show that disclosure of traders' identities accelerates price discovery. Flood, Huisman, Koedjik and Mahieu (FHKM) (1999) compare two markets with different degrees of transparency and show that the opaque market is more informational efficient and less liquid. In this experiment, however, the two markets differ not only in pre-trade transparency but also in market structure, one being an automated continuous auction, the other a bilateral screen-based dealer market. It follows that the result, a trade-off between transparency and liquidity, can be explained by the search costs associated to price discovery in the dealer market. In fact, Bloomfield and O'Hara (1999) show that when market structure is controlled for the trade-off disappear. Finally, Bloomfield and O'Hara (2000) find a prisoner's dilemma, which explains the coexistence of transparent and anonymous markets: all market makers would be better off under the transparent regime since they could collude and charge wider spreads, but there also exists an incentive to deviate to the opaque markets.

Both observation of real markets and empirical evidence (Massa and Simonov, 2002) show that there exists a high degree of information asymmetry among liquidity providers, so our framework posits asymmetric information. And unlike previous experimental works on market transparency, the present study inserts a market for information at the start of each round of trading in which participants can buy a signal about the liquidation value of the asset. This allows us to make the number of informed liquidity providers endogenous. Previous experiments on market transparency assume homogeneous information among market makers who trade with both insiders and uninformed liquidity traders. In this setting one can capture only transparency effects on the adverse selection premium required by market makers trading against insiders, not its effects on the incentive to acquire information, which can only be highlighted assuming asymmetrically informed market makers. An exception is Bloomfield, O'Hara and Saar (2002), who design an experimental asset market as an electronic limit order book with informed and uninformed traders placing limit and market orders. This insightful study does not address pre-trade transparency, but it shows experimentally that informed agents can play a key role in supplying liquidity. In line with the theoretical analysis underlying our experiment, the economic interpretation of these results is that informed agents are in a good position to supply liquidity, as they have no adverse selection costs.

Our experiment differs from FHKM in that we control for the market structure by assuming the same automated continuous auction market for both transparency and anonymity. Moreover, instead of including informed robots, the experiment posits informed human traders. This subtle feature is crucial to the interpretation of FHKM's results. If insiders are robots programmed to trade only on their private information and to trade extremely frequently, as in FHKM, at the start of each round market makers can effectively narrow the spread, being practically sure of capturing insiders' demand. Finally, whereas in Bloomfield and O'Hara (1999) with transparency spreads are wider at opening, in our framework they are wider over the whole trading period.

This work also relates to the literature on the market for information, which focuses on the relationship between the number of insiders and market quality. In a one-period model, Subrahmanyam (1992) finds a non-monotonic relationship between the equilibrium number of risk-averse insiders and liquidity. Holden and Subrahmanyam (1992) extend the multiple periods Kyle's multiple-period model to include multiple strategic informed traders and show that aggressive trading reveals most of their private information is very rapidly. This reduces adverse selection costs for risk-neutral uninformed market makers and increases market depth. Similarly, Fishman and Hagerty (1992) demonstrate that under certain circumstances an increase in the number of insiders deters market professionals from acquiring information and trading. Our own experimental framework differs from the three models mentioned just now; we reproduce an electronic open book where liquidity is provided by both informed and uninformed traders. In this setting informed traders are the best liquidity providers, since they impose smaller adverse selection costs on liquidity traders. It follows that an increase in the number of informed traders reduces the price impact of a trade and therefore increases liquidity.

The experimental market is designed to fit the model described in Rindi (2002). Experimental results are consistent with the theoretical predictions, according to which transparency reduces the incentive to acquire information, the equilibrium number of informed traders and the liquidity of the market.

In Section 2 we outline the main features of the model; Section 3 describes the experiment, and Section 4 comments on our results.

2 Theoretical Benchmark

Following Rindi (2002), the market is centralized with N informed and M uninformed risk-averse competitive agents and Z noise traders. Noise traders' net demand, x, is normally distributed with zero mean and variance σ_x^2 . The future value of the asset traded is equal to:

$$F = S + \varepsilon$$

$$S \sim N(0, \sigma_S^2) \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2)$$

Within this framework two regimes of pre-trade transparency are considered: anonymity, with traders using only the current price to update their expectations on F, and transparency, with traders observing personal identities and using the informed traders' orders to infer the liquidation value of the asset.

Each informed trader has an endowment shock equal to I and observes, prior to trading, a signal, S, on the liquidation value. Under both anonymity and transparency, each informed trader's net demand is therefore equal to:

$$X_I = \frac{S - p}{A\sigma_\varepsilon^2} - I$$

where

$$I \sim N(0, \sigma_I^2)$$

Under anonymity, uninformed traders' demand is equal to:

$$X_U = \frac{E\left[F|\Theta\right] - p}{AVar\left[F|\Theta\right]} - I_U = -Hp - \Psi I_U$$

where Θ is the signal extracted from the current price p and I_U is the endowment shock,

$$H = \frac{1 - \dfrac{Cov(F,\Theta)}{Var(\Theta)}}{A\,Var\,(F|\Theta) + \dfrac{Cov(F,\Theta)}{Var(\Theta)}\frac{AM\sigma_\varepsilon^2}{N}} \text{ and } \Psi = \frac{1}{1 + \dfrac{M\sigma_\varepsilon^2\sigma_S^2}{NVar(\Theta)Var\,(F|\Theta)}}.$$

Under transparency, uninformed traders' demand is equal to:

$$X_U^T = \frac{E(F|\Theta') - p}{A\,Var\,(F|\Theta')} - I_U = -H^T p^T + \Omega\vartheta'_T - \Psi^T I_U$$

where ϑ' is the realization of X_I and $\Psi^T = 1$.

The anonymity and transparency regimes have respectively, the following linear rational expectation equilibrium price functions:

$$P^A = \lambda_A[\frac{N}{A\sigma_\varepsilon^2}S - NI - M\Psi I_U + Zx]$$

with $\lambda_A = \left(\frac{N}{A\sigma_\varepsilon^2} + M \frac{1 - \dfrac{Cov(F,\Theta)}{Var(\Theta)}}{A\,Var\,(F|\Theta) + \dfrac{Cov(F,\Theta)}{Var(\Theta)}\frac{MA\sigma_\varepsilon^2}{N}} \right)^{-1}$;

$$P^T = \lambda_T[(\frac{N + M\Omega}{A\sigma_\varepsilon^2})S - (N + M\Omega)I - MI_U + Zx]$$

with $\lambda_T = \left(\frac{N}{A\sigma_\varepsilon^2} + \frac{M}{AVar(F|\Theta'_T)} \right)^{-1}$.

The equilibrium number of informed traders is derived by equating the expected utility of each informed trader from speculating on the signal to that obtained by hedging the endowment shock :

$$E(U\{[(X_I - p)F + IF] - c\}) = E(U\{[(X_U - p)F + I_U F)$$

where c is the cost of the information.

Standard indicators of liquidity, volatility and informational efficiency are derived from the equilibrium price functions in order to compare the two regimes.

3 The design of the experiment

The experiment consists of a series of sessions each being a market preceded by a market for information in which traders can buy a signal of the liquidation value of the asset traded. We run 87 replications of the experiment under transparency and 83 under anonymity: a total of 170 sessions.

3.1 The asset market

Each replication involves twelve participants[3]. Liquidation value is either 0.8, 2, or 3.2 currency units with equal probability[4]. Trades are placed in an automated continuous double auction[5]. Three groups of agents participate: informed traders, who decide to buy the signal in the market for information, uninformed traders and six robots[6]. Each human participant has a computer screen (Figure 1)[7] and is visually separated from the others to avoid contact outside the market. They can observe current and previous quotes. In the transparent setting, personal markers are displayed beside the quotes: this is the only feature that differs between the anonymous and the transparent regime. At any time human traders are free to place limit or market orders in

[3]Except replications 32 through 95, which have only ten.

[4]In the experiment, we choose discrete liquidation values of the asset and hence simplify the learning process, which would be too slow under the assumption of normality.

[5]Markets were simulated by using ZTree software, devoloped by Zurich University to design economic experiments.

[6]In replications 1 through 95, participants are divided into two groups: 6 "uninformed" traders and 6 "potential informed" traders. The uninformed have to participate to each trading round and they do not have access to the market for information. The potential informed traders participate in the market for information and decide whether to buy the signal and enter the market or not to buy the signal and not trade.

[7]In boxes on the top the number of assets and of cash units in portfolio and the personal marker of the participant are displayed. In the first column on the left participants submit sell orders; in the second column on the left ask prices and personal markers of sellers are displayed and participants can accept the offers by clicking on the button at the bottom. In the first column on the right participants submit sell orders, in the second column on the right bid prices and personal markers of buyers are displayed and participants can accept the offers by clicking on the button at the bottom. In the middle column traded prices and personal markers of buyers and sellers are displayed.

unit quantities and cannot cancel orders once submitted. There are no short-sale restrictions or penalties. There is no upper or lower limit on a dealer's allowable securities in inventory. Robot traders act as liquidity traders: they are programmed to submit a buy or a sell order, with equal probability, every twenty seconds. Each trading round lasts 140 seconds.

3.2 The market for information

Each trading round is preceded by a market for information, where participants can buy a signal about the liquidation value of the asset at the cost of 1 currency unit. Traders who pay the price receive a signal indicating one of the possible liquidation values of the asset: the signal is correct with probability 2/3 and it is wrong with probability 1/3. In the transparent setting, informed traders' identities are publicly announced before the market opens, in the anonymous setting only the number of them.

3.3 Subjects and incentives

The experimental subjects were 80 undergraduate students in Economics and Finance and the experiment was conducted within the course "Microstructure and Capital Markets", held at Bocconi University. Students were di-

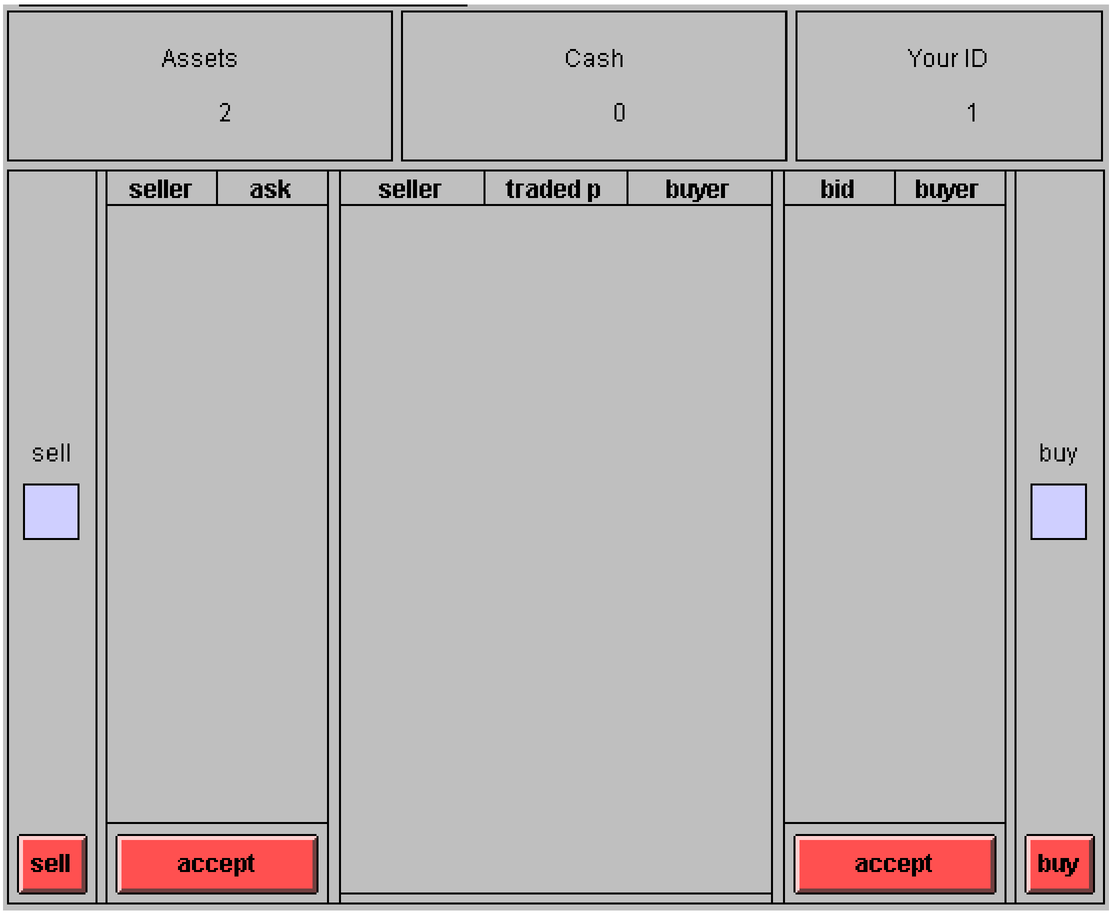

Figure 1: Trading screen in the transparent market

vided into 5 cohorts of 12 and 2 cohorts of 10; each cohort participated, on average, in 20 replications, under both the market regimes. The trading rules were explained in a 30-minute preparatory session[8]: during this period participants can ask questions in order to understand the trading mechanism, but these questions cannot concern possible trading strategies. Two pilot markets were conducted to help students familiarize themselves with the continuous auction software.

Participants receive a pre-trade endowment, which amounts to either 0, 1, -1, 2, -2 asset units with probability 6/10, 1/10, 1/10, 1/10, 1/10 respectively for the informed and 0, 1, -1, 2, -2 asset units with probability 6/10, 1/20, 1/20, 1/10, 1/10 respectively for the uninformed[9]. Traders are instructed to maximize their end-of-round wealth by trading the security. End-of-round wealth, W_i, equals the cash balance at the end of the round plus the security portfolio valued at the liquidation value of the asset less the price paid for the additional signal:

$$W_i = C_i + n_i v - c(i),$$

where W_i is the end-of-round wealth of trader i; C_i is the end-of-round cash

[8]The instructions distributed to market participants are given in the Appendix

[9]In replications 1 through 95 uninformed traders receive no endowment shock.

of trader i; n_i is the number of securities held by trader i at the end of the trading period; v is the liquidation value of the asset; c is the cost of information and $c(informed) = 1$, $c(uninformed) = 0$. End-of-round wealth for the potential informed trader who does not participate in the market for the security is equal to the pre-trade endowment valued at the liquidation value of the asset, i.e. $W = nv$.

In order to induce agents to maximize wealth, it is necessary to give value to experimental cash and securities through an incentive scheme. In our experiment, for each cohort, we ranked traders according to their end-of-period wealth and we gave a bonus point to the six scoring the highest wealth. The bonus point was valid towards the students' grade on the Microstructure and Capital Market exam[10]. A possible criticism of this incentive scheme is that traders who do not fare well in the first rounds might gamble for resurrection subsequently; i.e. not maximize expected utility. A similar argument holds for traders who do very well in the first rounds[11]. We checked the robustness of our incentive scheme by looking for the gambling strategies undertaken by all traders in all trading rounds; we found no correlation

[10] Other experiments (Kormendi and Plott (1982), Biais and Pouget (1999)) use also exam bonuses as rewards.

[11] We thank Martin Weber for pointing out this feature.

between gambles and traders' extreme profits and losses.

4 Results

Following the model's predictions, we can test four hypotheses on market behaviour by comparing the results of the experiment with numerical simulations for the model. First, we discuss the role of the market for information; second, we consider liquidity; third, we compare volatility under transparency and under anonymity; finally, we analyze the effects of disclosing traders' identities on informational efficiency.

4.1 Relating the experiment to the model

Assuming that M and Z are equal to 6, we are able to derive all the market parameter values corresponding to the experiment design[12]: $M = 6$, $Z = 6$,

[12]Considering the distribution of the endowment shock, the variance of the endowment shock (σ_I^2) for the informed is equal to 1 and the variance for the uninformed (σ_U^2) is equal to 0.9. The variance of the robots' orders (σ_x^2) is equal to 1, since robots submit a buy order ($x = 1$) or a sell order ($x = -1$) with equal probability.

Finally, the variance of the signal and the noise term (σ_s^2 and σ_ε^2) are calculated as follows. In accord with the model, s can be interpreted as the informed traders' expectation of the liquidation value, given the signal. Therefore, s can assume 3 values with equal probability: $s_1 = E(F|signal = 3.2)$; $s_2 = E(F|signal = 2)$; $s_3 = E(F|signal = 0.8)$. By using Bayes's rule it is easy to show that: $s_1 = 3.2\frac{2}{3} + 2\frac{1}{6} + 0.8\frac{1}{6}$; $s_2 = 2\frac{2}{3} + 3.2\frac{1}{6} + 0.8\frac{1}{6}$; $s_3 = 0.8\frac{2}{3} + 2\frac{1}{6} + 3.2\frac{1}{6}$. σ_ε^2 is obtained as the difference between the variance of the liquidation value of the asset ($\sigma_F^2 = 0.96$) and σ_s^2.

$\sigma_{\varepsilon}^2 = 0.72$, $\sigma_s^2 = 0.24$, $\sigma_I^2 = 1$, $\sigma_x^2 = 1$, $\sigma_U^2 = 1$. We also assume that the coefficient of risk aversion, A, is equal to 1. Table 1 reports the results of the numerical simulations for the following indicators of market quality: liquidity, volatility and informational efficiency.

4.2 The Experimental Dataset

We focus on four variables: the equilibrium number of informed traders; the inside spread quoted , defined as the average difference between the best ask and the best bid price; the mean absolute deviation between the transaction price and the liquidation value (MAD); the standard deviation of transaction prices (STD). In order to capture the evolution of the variables through the trading period, we split the trading round into 14 intervals of 10 seconds and we pool the data from both markets. During the first two trading intervals no one trades; for this reason we consider only the last 12 intervals.

4.3 The market for information

Hypothesis 1. Transparency reduces the equilibrium number of informed traders

The average proportion of informed agents in the anonymous regime

(0.65) is higher than under transparency (0.54). In order to identify the factors that induce traders to acquire information, we run the following regression:

$$N = \beta_0 + \beta_1 PI + \beta_2 TR + \varepsilon;$$

where N is the proportion of informed traders; PI is a dummy (1 for transparency, 0 for anonymity); TR is the number of the round considered. The results of the regression are given in Table 2: the estimate of β_1, the coefficient that measures the effect of disclosing traders' personal markers on the proportion of informed agents, is negative and significant[13].

The results of the experiment confirm *Hypothesis 1*: in the transparent market the number of agents who decide to buy the signal is lower than in the anonymous one. Plugging the experimental values into the model's parameters, the simulations show that the equilibrium number of informed traders in the transparent market ($N = 3$; $N(R1) = 3$) is smaller than in the anonymous market ($N = 5$; $N(R1) = 4$). The economic intuition behind this result is that when traders' personal markers are displayed, uninformed

[13]In all regressions, the standard deviation of the residuals is computed by using the Newey and West (1987) HAC covariance estimator.

traders free-ride on the informed traders' private information, thus lessening the incentive to acquire the signal.

Free riding is documented by the data for the continuous auction: the average time that elapses before an order placed by an informed trader is improved is less in the transparent market (14.3 seconds) than in the anonymous market (22.14 seconds). The following regression is run to analyze the differences in price improvement:

$$AT = \beta_0 + \beta_1 PI + \beta_2 TR + \varepsilon;$$

where AT is the average time before an order submitted by an informed trader is improved; PI is the regime dummy (1 for transparency, 0 for anonymity); TR is the number of the trading round. The estimate of β_1, the coefficient that measures the effect of transparency on the speed of price improvement, is given in Table 3: it is negative and significant.

4.4 Liquidity

Hypothesis 2. Transparency reduces liquidity

We measure liquidity by the inside spread: Figure 2 shows the pattern of

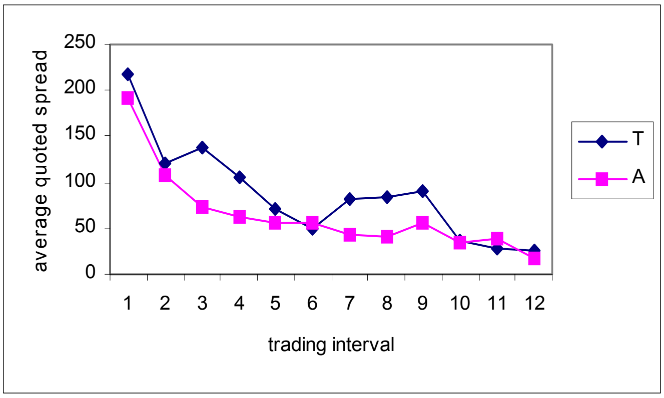

Figure 2: Average spread quoted over the trading intervals; T denotes transparency and A anonymity.

the average inside spread quoted over the trading intervals.

The average spread under anonymity (73.49) is smaller than under transparency (97.82). To test for the significance of this difference, we run the following regression:

$$QS = \beta_0 + \beta_1 PI + \beta_2 t + \beta_3 TR + \varepsilon;$$

where QS is the inside spread quoted; PI is the regime dummy (1 for transparency, 0 for anonymity); t is the number of the trading interval considered; TR is the number of the round. The results from the regression are shown in Table 4. The estimate of β_1, which measures the effect of disclosure of traders' identities on liquidity, is positive and significant.

In order to check for the relation between the number of informed traders and liquidity, we conduct the following regression:

$$QS = \beta_0 + \beta_1 N + \beta_2 t + \beta_3 TR + \varepsilon$$

where QS is the average spread quoted; N is the proportion of informed traders; t is the number of the trading interval; TR is the number of the round considered. The results are given in Table 5. β_1, which measures the impact of the proportion of informed traders on the spread, is negative and significant.

The results confirm *Hypothesis 2:* spreads are wider under transparency than under anonymity. The results are also consistent with the theoretical predictions, since if we plug the parameter values corresponding to the experimental design into the model, we find that transparency lowers liquidity ($Depth_T = 16.3908$; $Depth_A = 16.7867$; $Depth_T(R1) = 10.9536$; $Depth_A(R1) = 11.7042$;). The model provides an explanation for this result: since informed agents bear the lowest adverse selection cost, they offer liquidity to uninformed agents at the lowest price. This positive relationship between the number of informed agents and liquidity is documented by the regressions shown above. This is consistent with the results of Krahnen and Weber (2001), namely that when market makers face informational disadvantages, spread widen.

In our experimental markets, we find that informed traders provide more liquidity than uninformed: the average price improvement granted by informed agents (22.88) is greater than that offered by uninformed (14.74). The following regression compares the price improvement differential:

$$API = \beta_0 + \beta_1 INF + \beta_2 TR + \varepsilon;$$

where API is the average price improvement; INF is a dummy variable (1 if the price improvement is due to an informed trader, 0 if due to uninformed); TR is the number of the round. Table 6 shows that the estimate of β_1, which measures the effect of informed traders' quoting strategies on price improvement, is positive and significant.

4.4.1 Volatility

Hypothesis 3. Transparency influences volatility.

Our measure of volatility is the standard deviation of transaction prices. In Figure 3 we present the average standard deviation of transaction prices over the trading intervals. Figure 3 shows that volatility is greater under anonymity than under transparency. The average standard deviation of the transaction prices in the transparent market (27.71) is lower than with anonymity (38.09). To assess the significance of these findings, we run the following regression:

$$STD = \beta_0 + \beta_1 PI + \beta_2 t + \beta_3 TR + \varepsilon$$

where STD refers to standard deviation of prices; PI is the regime dummy (1 for transparency, 0 for anonymity); t is the number of the trading interval; TR is the number of the round. Table 7 shows that β_1, which measures the impact of disclosing traders' identities on price volatility, is significant and negative.

Considering the model's results, we conjecture that there exists a relationship between the number of informed traders and market volatility and also run the following regression:

$$STD = \beta_0 + \beta_1 N + \beta_2 t + \beta_3 TR + \varepsilon$$

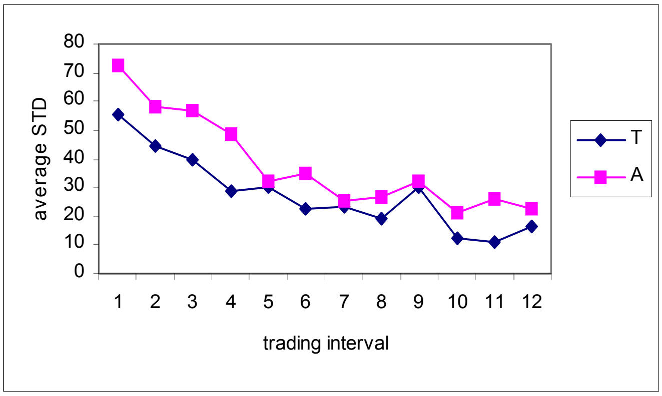

Figure 3: Average standard deviation of transaction prices over the trading invervals; T denotes transparency and A anonymity.

where STD is the standard deviation of prices; N is the proportion of informed traders; t is the number of the trading interval; TR is the number of the round. Table 8 shows the results: β_1, which measures the impact of the number of informed traders on volatility, is positive and significant.

We accept *Hypothesis 3*: our experimental results clearly indicate that transparency diminishes volatility. As far as the model is concerned, numerical simulations for the parameters corresponding to the experiment's design show that transparency influences volatility. ($STD_A = .27524$; $STD_T = .5639$; $STD_A(R1) = .5637$; $STD_T(R1) = .4176$). This behaviour can be explained by the different equilibrium numbers of informed traders under the two regimes. The model shows that there is a wide range of parameter values such that there exists a positive relationship between the equilibrium number of informed traders and volatility. This is confirmed by the experimental data. We also found a positive relationship between the proportions of orders submitted by informed traders and volatility through the following regression:

$$STD = \beta_0 + \beta_1 IO + \beta_2 t + \beta_3 TR + \varepsilon$$

where STD is the standard deviation of prices; IO is the proportion of orders submitted by informed traders; t is the number of the trading interval; TR is the number of the round. Table 9 shows the results. The estimate of β_1, which measures the impact of the proportion of orders submitted by informed traders on volatility, is positive and significant.

4.4.2 Informational efficiency

Hypothesis 4. Transparency influences informational efficiency.

We measure informational efficiency by the mean absolute deviation (MAD) between the transaction price and the liquidation value of the asset. Figure 4 plots the average MAD over the trading intervals. It is lower in the transparent market (70.63) than in the anonymous market (94.96).

To investigate the differences in the learning path between the two markets, we run the following regression:

$$MAD = \beta_0 + \beta_1 PI + \beta_2 t + \beta_3 TR + \varepsilon$$

MAD again standing for the mean absolute deviation of transaction prices from the liquidation value; PI is the regime dummy (1 for transparency, 0 for anonymity); t is the number of the trading interval; TR is the number of the round. As Table 10 shows, the estimate of β_1, which measures the impact of disclosing traders' identities on the mean price error, is not significant.

We cannot accept *Hypothesis 4*. In our experiment transparency has no significant effect on market efficiency. According to the model with endogenous information acquisition, transparency has two opposite effects on informational efficiency. On the one hand, it increases it, since uninformed traders get a more accurate signal of liquidation value. But at the same

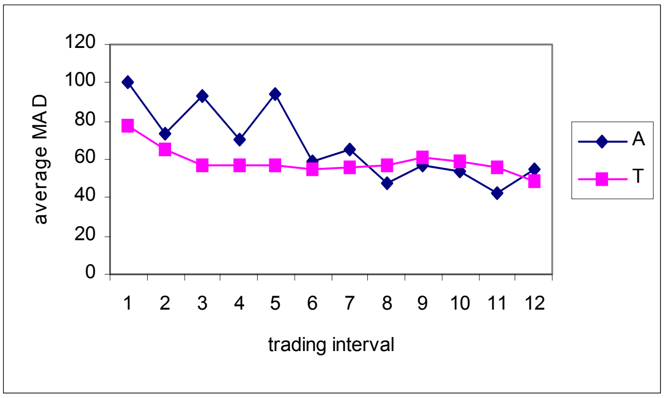

Figure 4: Average MAD over the trading intevals; T denotes transparency and A anonymity.

time it lowers the equilibrium number of informed traders, which means that when informed traders hold heterogeneous signals, it reduces informational efficiency. In our experiment informed traders hold homogeneous signals, so the second effect vanishes. This is why, according to the model's predictions, we should expect an increase in information efficiency under transparency. With the parameter values corresponding to the experimental design, simulations from the model show that information efficiency under anonymity ($EFF_A = 1.0751$; $EFF_A(R1) = .8119$) is lower than under transparency ($EFF_T = 1.1310$; $EFF_T(R1) = .877145$). In the experiment, however, we do not find these results.

Nevertheless, the experimental results confirm the intuition that in the transparent setting uninformed traders make better forecasts of the liquidation value than under anonymity. In fact, considering only trades by uninformed agents, we find that the average MAD under transparency (68.50) is lower than under anonymity (97.04). The following equation is estimated to assess the significance of this difference:

$$MAD(u) = \beta_0 + \beta_1 PI + \beta_2 TR + \varepsilon$$

where $MAD(u)$ is the average MAD for trades by uninformed agents; PI is the regime dummy (1 for transparency, 0 for anonymity); t is the number of the trading interval; TR is the number of the round. Table 11 shows that the effect on price errors of disclosing personal markers, captured by the estimate of β_1, is negative and significant.

Conversely, the average MAD of trades by informed traders is lower (54.31) under anonymity than under transparency (58.26). We run the following regression to compare the difference in price errors:

$$MAD(i) = \beta_0 + \beta_1 PI + \beta_2 t + \varepsilon$$

where $MAD(i)$ is the average MAD reported for trades by informed agents;

PI is the regime dummy (1 for transparency, 0 for anonymity); t is the number of the trading interval; TR is the number of the round. Table 12 shows that β_1, the coefficient that measures the effect of transparency on the average MAD, is not significant.

5 Conclusions

This paper reports the results of two experimental asset markets designed to investigate how pre-trade transparency affects market quality. The results from the experiment confirm the predictions of our theoretical model, which compares price formation and market quality under anonymous and transparent markets. The market described by the model and reproduced in the experiment is an automated continuous double auction with three groups of players (informed, uninformed and noise traders). Traders' identities are displayed only under transparency. Each trading round is preceded by a market for information in which agents can buy a signal concerning the liquidation value of the asset. We find that transparency lowers the number of participants who buy the signal, reduces market liquidity and diminishes price volatility. These findings are consistent with the intuition that transparency reduces the incentive to acquire information and thus the number of informed agents. In this centralized market, where informed agents face no adverse selection costs, liquidity decreases with their number since they are the best liquidity providers. As the number of informed traders decreases, the number of information shocks also decreases and leads to a reduction in volatility.

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6 Appendix

6.1 Instructions to participants

The following text was distributed to the participants two days before the experiment:

MARKET DESCRIPTION

The market is organized as a continuous automated double auction for a single risky asset. The liquidation value of the asset is either 0.8, 2, or 3.2 currency units with equal probability. At any time participants can submit buy or sell orders and accept other participants' orders. There are no short-sale restrictions or penalties. There is no upper or lower limit on a dealer's allowable securities portfolio. The trading period lasts 140 seconds.

3 groups of traders participate: liquidity traders, informed and uninformed traders.

The activity of liquidity traders is simulated by robots (ID code=-10 for sell orders; ID code=-20 for buy orders). Every 20 seconds the robots place a buy or a sell order (at the best bid / ask price) with equal probability. The robots only submit orders; they are programmed not to accept human traders' orders.

Before the market opens, participants must decide whether to remain uninformed or to become informed by paying 1 currency unit for a signal which indicates, with probability 2/3, the liquidation value of the asset. All traders are initially endowed with 0, 1, -1, 2, -2 asset units with respective probability of 6/10, 1/10, 1/10, 1/10.

PROFITS

A number of trading rounds will be played. Your final wealth is equal to the sum of all end-of-round wealths. Participants will be ranked according to their final wealth. The six participants with the greatest final wealth will receive one bonus point, to be added to their grade on the "Microstructure and Capital Markets" examination.

1) Informed traders

The informed trader's end-of-round wealth is given by the sum of: residual cash, plus the number of assets held (valued at the realized liquidation value) minus the cost of the signal (1 currency unit).

2) Uninformed traders

The end-of-round wealth for the uninformed trader is equal to the sum of residual cash, plus the number of assets held (valued at the realized liquidation value).