Strategic experimentation in a dealership market[1]

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Abstract

We study the strategies of the market makers in the inter-dealer market. We show that market makers actively learn from the dealers they trade with and strategically react to the information content of the orders they receive. We identify "hiding" and "experimenting" as main types of market makers' strategies. We show how market makers may engage in experimentation by directly trading with other market makers in order to assess the informational content of the orders they receive. We provide empirical evidence of this, using a unique high-frequency dataset on the Italian Treasury Bond market disaggregated at dealer level.

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1 Introduction

Market makers learn not only by observing the informational content of the orders they receive, but also by experimenting through the placement of orders with other market makers. However, while experimentation is a topics widely analyzed in economics in general (Bergemann and Valimaki 1996, Bergemann and Valimaki 1997, Keller and Rady 1999, Bolton and Harris 1999, Moscarini and Smith 2000), it has been scarcely dealt with in financial markets. This is curious as financial microstructure can make use of the richness of high-frequency data to empirically estimate it.

We endeavor to bridge this gap by focusing on market makers' strategic behavior. In particular, we show under which conditions market makers engage in experimentation by directly placing orders with other market makers. We then use a unique high-frequency dataset on the Italian Treasury Bond market, disaggregated at dealer level, to provide empirical evidence of the way experimentation is used to assess the quality of the information contained in the orders received.

We focus on the Treasury Bond market as this is a market where information is more about liquidity shocks and shifts in demand than about fundamentals (Ito, Lyons and Melvin 1998, Cao and Lyons 1999). This makes it ideal to study market makers' reaction to order flows. Also, the existence of regularly spaced informational events (Treasury bonds auctions) provides an ideal experiment to test for market makers' information-related strategies.

Market makers are in general described as market clearing devices who react to the arrival of buy and sell orders, by changing the quotes they post. They may be motivated by temporary inventory imbalances and by the trade-off between the cost of stock-out and the cost of keeping the inventory (Amihud and Mendelson 1980, Ho and Stoll 1981, Hansch, Naik and Viswanathan 1998). Alternatively, they may act in order to minimize the losses resulting from the presence of traders with superior information (Glosten and Milgrom 1985, Kyle 1985). In both cases, scarce attention is paid to the fact that market makers can also directly place orders with other market makers.

Only recently has it been suggested that market makers may optimally choose not only their bid and ask prices, but also their trading strategies on the interdealer market (Lyons 1997). The so-called "hot potato" theory assumes that market makers try to adjust any undesired inventory imbalances by buying from or selling to other market makers. Market makers "pass orders along until they happen upon a market maker whose inventory discrepancy they neutralize" (Cao and Lyons 1999). That is, as soon as market makers are "hit" by an order, they attempt to neutralize its impact on their inventory positions by placing orders with other market makers. The process is assumed to be more or less mechanical, in the sense that the market makers do not consider the effects of their behavior on the other market makers they are trading with, nor the characteristics of the dealers placing the originating trade. However, market makers do react to new orders depending on their informational content and, therefore, on the identity of the dealers who are originating the trade. Indeed, given that each market maker has some priors on the degree of informativeness of the other dealers, an order from an informed dealer should prompt a reaction that differs from an order from an uninformed one.

This suggests strategic behavior. Given that trading allows the market maker not only to exploit the information contained in the orders he receives, but also to assess the value of such information by experimenting, a market may resort to trading in order to experiment. This implies revealing part of the information and using the reaction of the other market makers as a reliability check to assess its quality. Alternatively, if the market maker is very confident about the quality of the information, he may attempt to exploit this information without revealing it. In the former case, the market maker *experiments* to better learn the value of the information received. In the latter case he *hides* his information. Experimentation is therefore a crucial component of a broader strategy set of the market maker.

However, while the process of passive learning based on filtering the information contained in the orders received has been properly investigated (Kyle 1985, Kyle 1989, Madhavan and Smidt 1991, Dutta and Madhavan 1997), experimentation has rarely been considered. Only Leach and Madhavan (1992, 1993) suggest a model of market makers' experimentation based on the optimal change of bid-ask quotes. But, the role played by active trading - i.e. the decision of the market maker to place an order with another market maker - in experimentation has never been addressed. Furthermore no empirical investigation is carried out to test for market makers' experimentation and its relevance for financial markets.

The goal of this paper is analyze the way market makers deliberately choose to trade with other market makers in order to experiment about the quality of the information they learn when an order is placed with them.

The paper is organized as follows. We provide the model in Section 2, outline the empirical restrictions in Section 3 and describe the market in Section 4. Sections 5, 6, 7 and 8 are devoted to the empirical estimation of the main testable restrictions. A brief conclusion follows. To spare the reader the technical details, we provide the proofs of the propositions, the description of the econometric approach and the numerous robustness checks of the reported estimations in the Appendix.

2 The Market Maker's Problem

We focus on the choice of a market maker who has received an order and deals with the problem of exploiting the information potentially contained in such a trade. He faces a trade-off: on the one hand he can exploit the information without revealing it. He can do so by directly placing an order with another market maker without changing the posted bid and ask quotes. On the other hand, by keeping the quotes unaltered, he risks being hit by a dealer at a price not in line with his new information. On the basis of these considerations, we propose the following description of the market maker's decision-making process. Figure 1 gives a stylized representation of it.

Let us consider a market maker who receives an order at the ask. First, he evaluates the informational content of the trade. If the market maker infers that the price will rise, he can exploit this information by buying directly from another market maker ("endogenous trade"). In this way he reveals his information only to a subset of the market. However, in order to do so, he has to keep the bid and ask quotes unchanged, at the risk of being hit at the misaligned ask by another dealer who has acquired the same information. The maximum loss would be equal to the posted depth multiplied by the difference between the ask and the expected value of the asset (conditional on the new information contained in the incoming order).

Alternatively, the market maker could increase the bid in order to induce a new transactions ("exogenous trade") that would reconstitute the inventory and, at the same time, raise the ask to fend off new orders. However, in this case, the change of the bid and ask quotes would immediately reveal the information ((Garbade, Pomrenze and Silber 1979)). If the new buy order were exactly equal to the expected value, the market maker would gain only the profit allowed by the bid-ask spread.

The market maker could also use a combination of the two strategies. That is, he could change the bid and ask quotes only partially, less than the expected change in prices, while also directly placing orders with other market makers. In this case, the effect on prices would be due to both the change in the bid and ask quotes (exogenous trade) and the impact of the endogenous trade, each weighted by the quantity traded.

The next step is the choice of counterpart. If the market maker decides to place orders directly with other market makers, he has to optimally select which one to approach. Indeed, if he wants to hide his information, he should select the counterparts so as to minimize the informational impact of his trade. In this case, he would place his order with a *less informed market maker.* This is similar in spirit to the dual-capacity trading of dealers in futures market considered, among others, by Roell (1990) and Fishman and Longstaff (1992).

If, however, the market maker is not very confident about the quality of information contained in the order received, but still believes it to have some content, he can decide to learn more about it. This could be the case if the market maker has noticed in previous trades that the dealer placing the order frequently, although not consistently, has correctly timed the market. Then, he may decide to place orders directly with other market makers, just to observe their reaction to the trade and to learn from it.

Unlike the case in which the market maker is very confident about the quality of the information, however, he would trade with the market makers he thinks are *more informed just to test their reaction*. We could therefore say that he is "experimenting". That is, the market maker checks the quality of his information by observing the reaction of the market makers he trades with and seeing if they change the bid and ask quotes, or if they simply limit themselves to placing orders with other market makers. Depending on which behavior prevails, hiding or experimenting, we can classify the market makers in different groups: "sneakies" if they always hide, "sleepies" if they hide only when they are very confident about the quality of the information and "skeptics" if they always experiment.

If there were no strategic behavior, the informational content of the transaction would

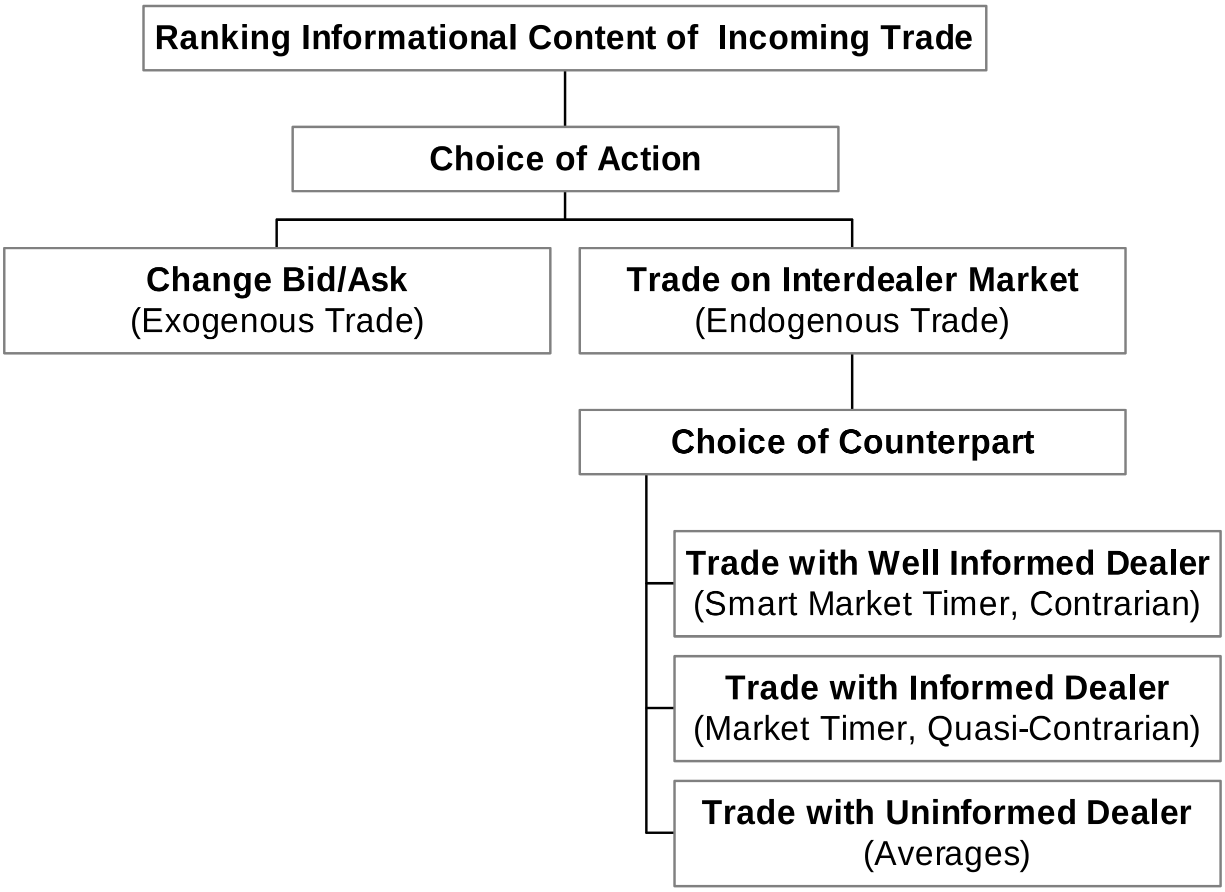

Figure 1: The decision process of market maker.

be reduced to zero and we would revert to the "hot potato" model. Indeed, the fact that the "tedious passing of undesired positions" (Cao and Lyons 1999) has no informational content can be justified in terms of trading taking place among equally informed dealers.

We consider market makers heterogenous in terms of risk aversion. The generic market maker is endowed with an exponential utility function $u(t, \Pi) = -e^{-\phi t - r\Pi}$, where r is the degree of risk aversion, ϕ is the intertemporal rate of substitution and Π is the profit he generates by trading. The market maker receives an order and has to decide how to react to it by either trading with informed market makers (informed endogenous trade q^i), or trading with uninformed market makers (uninformed endogenous trade q^u) or changing the bid-ask prices in order to stimulate trade (exogenous trade q^{exo}). We make the simplifying assumption that at each round of trade only one unit of asset is traded and the total trades (q^i, q^u and q^{exo}) add up to the order received (normalized to 1). Market maker's profits are:

$$\Pi = \Pi_1 - \Pi_2 + \Pi_3 \tag{1}$$

where Π_1 is the part of the profits generated by the exploitation of the better information, Π_2 is the cost incurred by keeping the bid and ask quotes unchanged and Π_3 is the profit generated by changing the bid and ask quotes.

The part of market maker's profit that is due to the exploitation of better information can be represented as the difference between the value of the asset and its price multiplied by the quantity traded (q). That is: $\Pi_1 = q^{endo}(v - p) = q^{endo}s^*$, where v is the true value of the asset and p is the price at which the trade is executed (Kyle 1985, Roell 1990).

The cost of keeping the bid and ask quotes unaltered can be represented as: $\Pi_2 = \zeta q^{exo}$, where ζ is the cost of being hit at the misaligned quotes. It is proportional to the difference between posted price and expected value. This cost can be thought of as the probability of being hit by another dealer at the misaligned quotes weighted by its cost.

The market maker can reduce the cost by changing the posted bid and ask prices. This would generate exogenous trade, but at a price already in line with the expected value. $\Pi_3 = q^{exo} * BA$, where BA is the gain that the market maker makes by changing the bid-ask, standardized per unit of incoming trade. BA is equal to the sum of two gains: the one due to the bid-ask spread (θ) and the avoidance of the loss that would have occurred if the market maker had been hit at the misaligned quotes (ζ). The intuition is that exogenous trade is a sort of stop-loss strategy that provides the market maker with a "normal" profit equal to the bid-ask spread. If we redefine profits after netting out the cost of not changing the bid and ask quotes represented by Π_2, we have:

$$\Pi = q^{endo}s^* + q^{exo}\theta,$$

Given that the market maker can choose to trade either with more informed market makers (q^i) or with less informed ones (q^u), the quantity traded endogenously can be expressed as: $q^{endo} = (q^i + q^u)$.

The difference between market price and asset value is affected by the price impact of market maker's trading. In particular, s^* is a negative function of the price impact: the more the market maker trades, the more he reveals information about the true value of the asset and reduces the spread between the price of the asset and its value. We assume that such a difference follows a stochastic process:

$$ds^* = \mu(1 - \lambda^{exo}q^{exo} - \frac{\lambda^i}{\sigma^2}q^i - \frac{\lambda^u}{\sigma^2}q^u)dt + \sigma dz, \tag{2}$$

where μ represents the difference between the value of the asset and its market price if the market maker did not trade, that is the potential profits of the market maker. The behavior of μ is described by a Poisson process that can take up two values: high (μ_H) and low (μ_L). The probability transition matrix between time t and time $t + dt$ is:

	μ_H	μ_L
μ_H	$1 - \vartheta dt$	ϑdt
μ_L	ϑdt	$1 - \vartheta dt$

(3)

Also, λ^{exo}, λ^i and λ^u represent the impact on price of exogenous trade, informed endogenous trade and uninformed endogenous trade respectively.[1] The market maker is fully

[1] Indeed the higher the spread, the less the dealers is willing to reduce it through their own trading and, therefore, reduce experimentation. It is worth noting that this feature results from the fact that the cost of experimenting is proportional to the spread ($\mu(1 - \lambda^i q^i - \lambda^u q^u)$). The alternative specification ($\mu - \lambda^i q^i - \lambda^u q^u$) would produce the same results, except for the fact that the expected value of the asset would not affect the decision to trade with informed market maker. We think that this specification better captures the fact that the higher the payoff is, the greater the impatience of the dealer should be, and the weaker his desire to experiment.

aware that exogenous trade has a stronger impact on prices than does endogenous trade. He also knows that placing an order with a more informed market maker has a stronger impact on prices than placing an order with a less informed one. The reason is that informed traders already have an information set which allows them to exploit the additional information. Therefore, $\lambda^{exo} > \lambda^{i} > \lambda^{u}$.

Given that changing the bid and ask quotes reveals most of the information, we assume, that $\lambda^{exo} = 1$. We also assume, with no loss of generality, that $\lambda^{u} = 0$. The price impact of endogenous trade depends on the market volatility. The higher volatility is, the more the market maker will be able to camouflage his trade. On the contrary, exogenous trade reveals information to the rest of the market regardless of market volatility. On the basis of these assumptions, we can write the law of motion of profits as:

$$d\Pi = \mu(1 - q^{exo} - \frac{\lambda^{i}}{\sigma^{2}} q^{i})(q^{i} + q^{u})dt + \theta q^{exo} dt + \sigma(q^{i} + q^{u})dz. \tag{4}$$

It is important to note that in what follows we do not make any attempt to solve for equilibrium λs. Instead, we focus on deriving testable predictions about the behavior of the individual market maker under the assumption of heterogeneity of market makers' reaction to his trade.

Also, we will show that differences in risk aversion are enough to induce some market makers to experiment and others to hide. This implies that at equilibrium the informational content of the incoming orders is always positive. The mere fact that some agents willingly release part of their information through experimentation justifies the fact that at equilibrium market makers are able to rank each others in terms of the informational content of their trades.

2.1 The Market Maker's Learning

Up to now we have assumed that the market maker knows the true value of μ. In this case, the decision simply involves a trade-off between exploiting the information about the expected value of the asset and incurring a cost due to the impact of trading on market price. However, if the market maker is not fully informed, the decision problem changes drastically. Indeed, the market maker can now learn by observing the reaction of other market makers to his orders. This means that trading provides him with a way of experimenting and updating his beliefs on the quality of the information contained in the order received. In particular, we assume that each unit of the incoming trade the market maker receives contains a signal (ξ) about the underlying value of the asset. Such a signal is an unbiased predictor and follows the process:

$$d\xi = \mu dt + \frac{\sigma_\xi}{\sqrt{\frac{1+q^i}{\sigma^2}}} dz, \tag{5}$$

where dz is the noise of the signal and σ_ξ is its diffusion coefficient.

The market maker can reduce the noise by experimenting. That is, he can assess the quality of the signal by trading with other, potentially more informed, market makers. Therefore, the informativeness of the signal is positively related to the "informed trading" of the market maker (q^i). His capacity to learn by placing orders with other market makers depends also on the overall market volatility (σ). The higher the market volatility, the less informative is the reaction of the market maker he trades with. We can therefore define the law of motion of market makers' beliefs on μ.

Proposition 1 *The evolution of the posterior probability of the regime μ_H is:*

$$d\pi_{\mu_H} = \mu_{\pi_{\mu_H}} dt + \Sigma d\nu, \tag{6}$$

where

$$\begin{aligned} \mu_{\pi_{\mu_H}} &= (1 - 2\pi_{\mu_H})\vartheta,\ \Sigma = \left(\frac{\pi_{\mu_H}(1 - \pi_{\mu_H})(\mu_H - \mu_L)}{\sigma_\xi^2}\right) \textit{ and} \\ d\nu &= \left(\frac{ds}{s} - \left[\pi_{\mu_H}\mu_H + (1 - \pi_{\mu_H})\mu_L\right] dt\right), (\textit{proof in Appendix A}). \end{aligned}$$

Σ represents the flow value of information. It can be rewritten as $\Sigma = \frac{I_i(\mu_H - \mu_L)}{I_o}$, or , if we take the logarithm,

$$\ln(\Sigma) = \ln(\mu_H - \mu_L) - (\ln(I_o) - \ln(I_i)) = \ln(\mu_H - \mu_L) + \Delta \tag{7}$$

where Δ can be loosely defined as the differential in information between incoming and outgoing trade. It represents the increase in informativeness due to trading with informed market makers. The market maker, after having received an order has beliefs whose accuracy depends on the noise of the signal (σ_ξ^2). By placing orders with informed market makers (q^i) the dealer improves the accuracy of his beliefs. The greater accuracy is represented by a tighter distribution of the posterior (smaller $\pi_{\mu_H}(1-\pi_{\mu_H})$). We can think of this as if the market maker were using the reaction of the informed market makers to his orders as a reliability check for the information he has received with the incoming trade.

2.2 The Market Maker's Optimal Trading Strategy

The market maker solves the following problem:

$$Max_{q^i,q^u,q^{exo}}\left[E\int_0^\infty[-e^{-\phi s}U(\Pi_s)ds]\right] \tag{8}$$

$$s.t. \quad : \quad q^i+q^u+q^{exo}=1 \tag{9}$$

Using the fact that $1>\lambda^i>0$, let's define $x=1-\lambda^i$, that is the difference in impact that trading endogenously with informed market makers produces as opposed to changing the bid and ask quotes. The value function of the market maker can then be expressed as:

$$J=J_w(1-q^{exo}-\frac{(1-x)}{\sigma^2}q^i)(q^i+q^u)\widehat{\mu}+\theta q^{exo}J_w+\frac{1}{2}J_{ww}(q^i+q^u)^2\sigma^2+\frac{1}{2}J_{\pi\pi}(\frac{1+q^i}{\sigma^2})\Sigma+J_t, \tag{10}$$

where $J_w>0$, $J_{ww}<0$ and $J_t<0$. $J_{\pi\pi}$ is the second derivative of the value function with respect to information and is always positive. We see immediately that the market maker faces two trade-offs. The first one is between the gain from experimentation ($\frac{1}{2}J_{\pi\pi}(\frac{1+q^i}{\sigma^2})\Sigma$) and the cost incurred to experiment. This cost consists of the of lower expected return due to the impact of market maker's own trading on prices ($-J_w\frac{(1-x)}{\sigma^2}q^i(q^i+q^u)\widehat{\mu}$). The cost increases with the expected returns ($\widehat{\mu}$) and with the impact of trading endogenously with informed market makers ($-x$) and decreases with market volatility (σ^2). The higher the expected return and the stronger is the price impact, the more costly it becomes to forego part of it by revealing information through experimentation. On the other hand, the higher the volatility, the lower the price impact and therefore the lower the cost of experimenting.

The second trade-off is the one between the benefits of going exogenous (θq^{exo}) and the cost of doing so ($-J_w q^{exo}(q^i+q^u)\widehat{\mu}$). This cost is again expressed in terms of foregone profits and, as before, is a direct function of market expected returns ($\widehat{\mu}$). Solving the optimization problem defined in equations 8 and 9 we can define the optimal amount of experimentation.

Proposition 2 *The optimal amount of trade with the informed market makers is:*

$$q^i = \sigma \frac{2\widehat{\mu}\left[(x-1)r\theta + J_{\pi\pi}\Sigma\right] - r\sigma\Sigma J_{\pi\pi}}{2\widehat{\mu}^2 r(x-1)^2}.$$

3 Empirical Restrictions

The model contains testable restrictions. We use these to determine whether market makers learn from the orders they receive and if they react selectively and strategically to the ones characterized by higher informational content. In particular, we want to test whether experimentation is one of the strategies market makers play.

Hypothesis 1: Market makers resort to endogenous trade more frequently in case where they receive privileged information.

If the decision of the market maker to place orders directly with other market makers is mainly information-driven, we should observe *market makers resorting to endogenous trade more frequently in cases where they receive privileged information.* From Equation (7) it follows that:

$$q^{endo} = q^i + q^u = \frac{J_{\pi\pi}\Sigma}{2\widehat{\mu}r(1-x)} = \frac{J_{\pi\pi}\Sigma}{2\widehat{\mu}r(1-x)} \frac{I_i(\mu_H - \mu_L)}{I_o} = f(I_i). \tag{11}$$

This implies a *positive relationship between the decision of going endogenous and the informativeness of the incoming trade* (I_i). The opposite is true for exogenous trade which is:

$$q^{exo} = \sigma \frac{2\widehat{\mu}(1-x)r - J_{\pi\pi}\Sigma}{2\widehat{\mu}r(1-x)} = f(-I_i). \tag{12}$$

That is, information-driven trades should have higher power to explain endogenous trades than to explain exogenous ones. Indeed, if the market maker only wants to rebalance his inventory, he can simply change the bid and ask quotes. Endogenous trade, however, also presents the market maker with the opportunity to exploit his information. This implies that inventory-rebalancing should be mainly related to exogenous trading, while information-exploitation should be more correlated to endogenous trading. Therefore, the decision to trade endogenously should be strongest in the case where the incoming trade is very informative, and weakest in the case where the incoming trade is uninformative.

Hypothesis 2: Market makers' strategic behavior on the secondary market should change at the time of the auction.

The strategic behavior of the market maker should change when some informational event modifies the difference in cost between trading endogenously and trading exogenously (x). The incentive to trade exogenously is a function of x:

$$\frac{\partial q^{exo}}{\partial x} = -\frac{J_{\pi\pi}\Sigma}{2\widehat{\mu}r(x-1)^2} < 0. \tag{13}$$

That is, exogenous trade drops when the difference between the cost of going exogenous and the cost of going endogenous (x) increases. In the case of the Treasury bonds market, the Treasury auction is the event when going exogenous is substantially more costly than going endogenous. Indeed, the auction provides some dealers with an information advantage as the market makers who intermediate the biggest share of bonds being auctioned off have additional information about the overall market demand schedule and liquidity shocks. At the same time, the auction also provides the informed dealers with a way of exploiting this information without revealing it. Therefore, changing the bid and ask quotes before the auction becomes more expensive as it reveals information that could be used profitably *both in the secondary market and at the auction.* This implies that in general we expect a *reduction of exogenous trade and an increase of endogenous trade the day before the auction.*

Also, the reaction should differ according to the ability of the market makers at the auction. The "more capable" market makers -i.e. the ones who have better information at the auction - can afford reducing both exogenous and endogenous trade, as they can meet the demand at the auction they intermediate. However, less capable market makers, being more uncertain about the results of the auction, have to trade in the secondary market in order to meet the demand of bonds they intermediate.[2] Therefore, we expect that in

[2] We deal with the case where the bonds on auction are completely identical and fungible to the ones already traded in the secondary market. This is indeed the case for the Italian market as explained in Section 4.

the period before the auction the more informed market makers drastically reduce any information-related trading activity, while the less informed ones channel most of their activity through less information-revealing endogenous trade.

Hypothesis 3: Market makers strategically select the other market makers to approach in order to either increase their information (”experimentation”) or hide it (”hiding”).

If order flows are informative and market makers react strategically to them, the decision to go endogenous entails the selective choice of the counterparts with whom to trade. A market maker reacting to the information contained in an incoming order has to decide how to use such information. If he is confident about its quality, he can try to ”hide” his information and exploit it by trading with a dealer less informed than the one who has hit him. Alternatively, the market maker may want to increase his informativeness and “experiment”, by placing orders with more informed market makers. We can therefore define two types of strategies: hiding and experimenting.

The net benefit of placing orders with informed market makers is a positive function of the flow value from experimentation (Σ). Using the definition of Δ (equation 7) we can relate the decision to place an order with informed market makers to the differential between the degree of informativeness of the dealer who is placing the order and that of the other market maker whom the ”hit” market maker is approaching. In particular, we have that:

$$\frac{\partial q^i}{\partial \Delta} = \frac{J_{\pi\pi}\sigma(2\widehat{\mu} - r\sigma)}{2\widehat{\mu}^2 r(x-1)^2}. \tag{14}$$

This implies that:

$$\frac{\partial q^i}{\partial \Delta} > 0 \text{ if } r \text{ is high and } \frac{\partial q^i}{\partial \Delta} < 0 \text{ if } r \text{ is low.} \tag{15}$$

That is, depending on the degree of risk aversion (r), market makers can be divided into two groups which we would call ”sneakies” and ”skeptics”. Skeptics place their trade with counterparts who are more informed than the ones whom they are receiving their orders from. Sneakies place their orders with counterparts who are less informed than the ones whom they are receiving their orders from. The intuition is that the former try to learn by hitting more informed market makers, while the latter only approach the less informed ones in order to hide their information. The skeptics are more risk averse and, therefore, attempt to learn. The sneakies are only concerned with profits and therefore attempt to hide their information to exploit it better.

Empirically this implies that, in the case of hiding, we expect a negative relationship between the degree of informativeness of the dealer who places the originating trade and the degree of informativeness of the market makers with whom the hit market maker places an order. In the case of experimenting, on the contrary, a positive relationship is predicted.

Hypothesis 4: Market makers' reaction to market volatility depends on the strategy they play. Volatility increases sneakies' informed endogenous trade and reduces skeptics's one.

In terms of the relationship with the market volatility the two classes of market makers display opposite behavior. In particular,

$$\frac{\partial q^i}{\partial \sigma^2} = \frac{\widehat{\mu}(J_{\pi\pi}\Sigma + r\theta(x-1)) - J_{\pi\pi}r\sigma\Sigma}{\widehat{\mu}^2 r(x-1)^2}. \tag{16}$$

This implies that:

$$\frac{\partial q^i}{\partial \sigma^2} < 0 \text{ if } r \text{ is high and } \frac{\partial q^i}{\partial \sigma^2} > 0 \text{ if } r \text{ is low.} \tag{17}$$

that is, higher uncertainty in the market has a negative impact on experimentation for the skeptics and a positive one for the sneakies. The reason can be found in the aversion to risk: the higher the volatility, the higher the risk, the less the skeptics experiment, and therefore the less they resort to endogenous trade. The opposite is true for the sneakies who, being less risk averse, use the opportunity provided by higher volatility to hide their trade better. This allows them to increase their endogenous trade.

4 The Market and the Dataset

In Italy, there are three main types of traded bonds: Treasury Notes, Treasury Bonds and financially indexed bonds. Treasury Bonds (Buoni del tesoro Poliennali, or BTP) are medium- and long-term coupon bonds. Financially indexed bonds (Certificati di Credito del tesoro or CCT) are medium-long term coupon bonds with the value of the coupon indexed to short-term Treasury Bills. Treasury Notes (Certificati del Tesoro a Zero Coupon, or CTZ) are 2-year zero-coupon bonds.

Bonds are mostly [3] traded on an inter-dealer based Treasury Bond Market (Mercato Telematico dei titoli di Stato, MTS). The MTS market is a screen-based system, operating between 9.00 a.m. and 5.00 p.m.

There are three types of dealers trading on the MTS: ordinary dealers (approximately 360), ordinary market makers (40) and "primary dealers" or "specialists"(16). Only banks, investment firms and insurance companies are allowed to act as dealers. Ordinary dealers may only place orders with market makers and cannot post bid and ask prices. Market makers commit themselves to continuously posting bid and ask prices. They may place orders with other market makers.[4] Specialists are market makers who must trade a minimum percentage of each type of bond on the secondary market and purchase a minimum percentage of the bonds being auctioned off at each auction. In exchange for operating within more binding trading requirements, they enjoy re-financing benefits, being entitled to borrow at a particular convenient rate at the discount window of the Bank of Italy.

Each single trader (ordinary dealer, ordinary market maker and primary dealer) has access to a screen where he can observe the bid and ask prices the dealers (both specialists and ordinary market makers) post and the maximum number of bonds they commit themselves to trade (depth). Market makers are not anonymous *ex ante*. That is, the name of the market maker appears on the screen next to the bid and ask prices he is posting.

While each dealer knows the identity only of the counterpart with whom he is trading, no market participant (ordinary dealer, ordinary market maker or specialist) knows the identities of other market participants involved in a transaction in which he is not directly involved. This makes MTS very similar to NASDAQ.

The transaction takes place only at the posted price. When it is executed, the name of the dealer "hit" blinks, signalling to the market that he is trading and listing the price

[3] Bonds are alos traded on the Milan Stock Exchange. However, the overwhelming majority of trade in Treasury Bonds takes place on the MTS. The number of bonds traded on the Stock Exchange is limited and prices reflect the ones determined in the MTS.

[4] They withdraw *temporarily* from the market if they receive an order equal to the maximum number of bonds they are commited to trade.

at which the trade takes place. The volume of the transaction is never revealed, except in the rare case when a dealer receives an order equal to the maximum number of bonds he has committed himself to trade. In that case, he automatically withdraws from the market for a period not longer than 60 seconds. [5] This withdrawal is the only signal the market receives about the size of the transaction.

Analogously to the FX market (Lyons 1995), the slow diffusion of information via interdealer trade is facilitated by the absence of trade reporting (even *ex post*). Only aggregate figures for the whole market are available at the end of the day. The screen-based system is transparent to the general public, and the best bid and ask prices are reported on a specific page by Reuters. [6]

The primary Treasury bond market is based on uniform type auctions. The schedule of the auctions is communicated by the Treasury at the beginning of the year, while the number of bonds that to be auctioned off is announced one week before. The official submission of the demands at the auction takes place through a computerized screen-based system. Each participant in the auction is informed of the amount he has been allotted, while the market as whole is informed of the total number assigned, the auction price and the cover ratio, that is, the ratio between the number of bonds demanded and the number allotted. To increase the depth of the market, the Treasury issues the same bonds repeatedly ("reopens the auction").

The dataset contains all the transactions from 29 September 1994 to 28 February 1996 for all the listed bonds (total of 37). In all, they total 1,393,437 transactions. For each transaction, we have data showing the time at which the transaction is executed, the size of the transaction, the price and the name of the counterparts and the identification of the dealer who originated the transaction. Descriptive statistics of the data are reported in Table 1.

[5] It can be estimated that on average this occurred less than 500 times in our sample.

[6] All the transactions are settled through a system owned and operated by a company that acts as a subsidiary of the Central Bank (SIA). The transactions are also continuously monitored by the Central Bank itself, which has to check if the dealers meet the requirements in terms of the continuous posting of bid-ask prices, the minimum number of transactions executed per category of bond and the size of the bid and ask spread. Given that the Central Bank also acts as a clearinghouse and provider of liquidity to the whole interbank payments settlement system, the creditworthiness of the dealers is implicitly guaranteed by the Central Bank itself.

To focus on the reaction of the market maker, we consider the transactions following the originating one. In particular, for each transaction, we consider all the transactions of the same market maker in the following 10 minutes. These comprise both the additional orders placed with the market maker (exogenous trade) and the orders that he places with the other market makers (endogenous trade). We define as endogenous trade the amount of trade on the *k-th* bond that is endogenously originated by the *j-th* market maker, when he places an order with other market makers. Exogenous trade, on the contrary, represents the amount of trade on the *k-th* bond that is not directly originated by *j-th* market maker. It could come to him either for market exogenous reasons or because it is induced by a change in the bid and ask quotes he posts.

The sample has been divided into "days before the auction" and "all other days". The estimates for "days before the auction" [7] are made only for the bonds that are auctioned the next day. All the estimations are carried out using Hansen's Generalized Method of Moments, with correction on the variance-covariance matrix to control for both heteroscedasticity and autocorrelation. In order to deal with the generated regressors in our estimations, we adopt the Pagan's (1984) approach based on instrumental variable estimation.

5 H1: Endogenous Trade and Information

5.1 A definition of the Informativeness of Trade

The informational content of the incoming trade can be inferred by looking at the dealer who has originated the trade. As Cox and Rubinstein (1985, p. 81) pointed out: " from perhaps bitter experience market makers learn to identify likely infirmation traders." That is, each market maker learns about the degree of the informativeness of the other market makers he is trading with by simply looking at the behavior of prices in the period following the transaction he effected with them. In particular, a dealer who consistently buys before prices rise and sells before they drop is classified as "informed". Trading allows the market maker to update continuously his priors on the degree of informativeness of

[7] The "days before the auction" are defined as the period covering the whole trading day before the auction and the morning of the auction before the deadline to submit the bids.

the other market makers and therefore on the informational content of the incoming trade, defined in terms of the dealer originating it. The priors on other dealers become the basis of market makers' assessment of the quality of information contained in the trade they receive. We will refer interchangeably to the informational content of trade and to the degree of informativeness of the dealer originating it. We look at the changes in prices of the same bond in the 5 minutes that follow each transaction and, for each market maker *j,* we run the auxiliary regression:

$$\Delta P_{k,t} = \gamma_{ji} T_{jik,t} + \varepsilon_{jik,t} \tag{18}$$

in a pairwise relation versus all the other i dealers *for each individual bond k.* We define $T_{jik,t}$ as the total number of signed trades received by the *j-th* market maker from the *i-th* dealer for the *k-th* bond at time t. $\Delta P_{k,t} = (P_{k,t+5} - P_{k,t})$ is the change in the price of the *k-th* bond in the 5 minutes following the transaction. Following Madhavan, Richardson and Roomans (1997), we use the actual transaction prices. The procedure we follow to identify trades with possible informational content is reminiscent of the statistical procedure that specialists use to identify the information-driven trade originated by the brokers at the NYSE (Benveniste, Marcus and Wilhelm 1992).

The coefficient γ_{ji} represents the degree of informativeness of the specific *i-th* dealer who is placing the order, as perceived by the *j-th* market maker.[8] A significant value of γ_{ji} implies that the dealer is informed. The greater the value of the coefficient, the higher the degree of informativeness of the dealer is, and the greater the informational content of the order received. [9]

In Table 2, we report the results of the estimation of Equation (18). They show evidence of an informational content of trades. In particular, if $\gamma_{ji} = 0.001$, for a lot of standard size of 5 billion lire, the expected price impact is of the order of 0.5 bp. The average price impact of a trade intermediated by a specialist is about 0.65 bp, while the price impact of a trade intermediated by an ordinary market maker is about 0.75 bp.

The dealers who are perceived as being more informed, both in terms of value of the

[8]To check the robustness of the results, we experiment with different "learning windows". For details, see Appendix B.

[9]To avoid problems due to thin trading, we consider only the values of γ_{ji} that are significant at the 5% level, and for the regression with at least 5 trades.

coefficient (γ_{ji}) and its significance (*t-statistics*), are the specialists. This fits with our intuition. Given that the specialists are the biggest traders, they are more likely to be informed. For the same reason, the degree of informativeness is lower for ordinary market makers and the lowest for ordinary dealers.

It is important to note that a statistically significant γ_{ji} captures the *temporary* informational advantage of the dealer i over dealer j at a given time. On average, the probability of given γ_{ji} to remain significant at 5% level after three days is only 0.496 and goes down to 0.177 in 10 days. Thus, specification (18) is capturing only the temporary informational advantage that is related to "semi-fundamental information" like order flows or liquidity shocks (Fleming and Remolona 1999).

5.2 First Test of Strategic Behavior

We can now test how this informational content is related to market makers' behavior. We consider a linear specification where endogenous as well as exogenous trade are directly related to the informational content of the incoming trade. The general test is:

$$s_{jk,t} = \alpha + \beta Q_{jik,t} + \delta I_{ji,t} + \zeta \sigma^2_{k,t} + \theta d_j + \varepsilon_{jik,t}, \tag{19}$$

where $s_{jk,t}$ is the ratio between endogenous trade and total trade of the *j-th* market maker for the *k-th* bond in the 10 minutes following the originating trade (time t). It represents the "share" of endogenous trade over total trade. $Q_{jik,t}$ is the size of the order which the *j-th* market maker receives by *i-th* dealer (the "originating dealer") for the *k-th* bond at time t.[10] $I_{ji,t}$ represents a measure of the degree of informativeness of the *i-th* dealer as perceived by the *j-th* market maker.

As alternative measures of the degree of informativeness of the market maker we consider: the value of the coefficient γ_{ji} (as estimated in Equation 18), its statistical significance (*p-value*) and the product between the two (γ_{ji} times *p-value*). The first proxy represents the degree of informativeness of the specific *i-th* market maker who is placing the order, as perceived by the *j-th* dealer, the second represents the degree of accuracy of the signal and the third proxies for the "expected" degree of informativeness of the dealer. $\sigma^2_{k,t}$ is a proxy of market uncertainty at the time when the market maker receives the

[10]Both trade and orders are expressed in absolute value.

incoming orders. It is defined as the variance on the *k-th* bond in the 10 minutes before the originating transaction, while d_j is a dummy that controls for market maker's idiosyncratic characteristics. Sampling is based on transaction time. The analysis is carried out disaggregated at the level of individual market makers.

The restrictions imposed by Equations (11) and (12) postulate that $\delta > 0$. That is, the incentive to trade endogenously increases with the degree of informativeness of the dealer who places the order. Or, the higher the informativeness ($I_{ji,t}$) of the trader placing the order, the more the market maker should react to his order by going endogenous.

Table 3, Panels A and B report the results both at the aggregate market level and grouped by type of dealer according to the institutional classification. They support the hypothesis of correlation between informational content of trade and the choice of going endogenous. The fact that ordinary market makers and specialists always prefer endogenous trade to exogenous trade is shown by the positive value of the coefficients (δ) and by the high significance of their *t-statistics*. Assuming the same price impact of the incoming transactions, the share of endogenous trade increases by 3% for a 1% improvement in the quality of the signal (as measured by *p-value*). The impact is somewhat larger for specialists (3.3%) and lower for ordinary market makers (2.5%).

6 H2: Strategic Behavior in the Proximity of the Auction

In the proximity of the auction, the explanatory power of the tests considered in the previous section should change. In particular, the restriction imposed by Equation 13) together with the assumption of different ability of the market makers *at the auction* requires δ not to be significant for the "more capable" market makers. For the less capable ones, instead, $\delta_{day\,before\,auction} > \delta_{non-auction\,days}$.

We assume that the specialists are the market makers more capable at the auction. Indeed, their size, their superior information obtained through their ability to intermediate a bigger share of demand at the auction and particular institutional arrangements with the Central Bank confer them a more powerful position at the auction.

The results, reported in Table 3, Panel B, confirm our hypothesis: the specialists reduce their information-driven trades. The ordinary market makers, instead, increase endogenous trading. For example, in the case the coefficient on the informativeness of incoming dealer is measured by using the *p-value* (I_{p-val}), δ goes from 2.5 to 4.75, with a strong increase in significance (the *t-statistics* jumps from 2.33 to 3.48).

It is interesting to note that the increase in endogenous trade is mostly made of trading placed with less informed dealers. Indeed, Table 4 shows that the days before the auction the ordinary market makers redirect their trade towards less informed market makers. This indicates that they choose to trade endogenously in order to hide and not to experiment. We will expand upon this point below.

7 H3: Market Makers' Strategies: Hiding vs. Experimentation

Testing the restriction imposed by Equation (15) requires us to identify the different strategies in terms of the reaction to the informational content of the incoming trade. We therefore focus directly on how the perceived degree of informativeness of the incoming trade affects the way the market maker chooses the counterpart whom to place his order with.

7.1 Testing the Existence of Differential Behavior

As a preliminary step, we test whether there is a pattern in the way market makers react to informed trade. In particular, we want to see whether there is a relationship between the informativeness of the dealer placing the originating order and the informativeness of the market makers whom the "hit" market maker is approaching. Therefore, we estimate:

$$s^i_{jk,t} = \alpha + \beta Q_{jik,t} + \delta I_{ji,t} + \zeta \sigma^2_{k,t} + \theta d_j + \varepsilon_{jik,t}, \tag{20}$$

where $s^i_{jk,t}$ is the ratio between endogenous *informed* trade and total endogenous trade of the *j-th* market maker for the *k-th* bond in the 10 minutes following the originating trade (time t). $Q_{jik,t}$, $I_{ji,t}$, $\sigma^2_{k,t}$ and d_j are defined as in Equation (19). Total informed trade is split in three groups, depending on the degree of informativeness of the market makers whom the hit market maker approaches after having received the order. We use the *p-value* of the γ_{ji} coefficient as defined in Equation (18) as a measure of market makers' informativeness. If there are rational strategies which can be traced from the data, the $\delta' s$ for the different groups should be different.

The results, reported in Table 4, Panels A and B, show that there is a significant change in the relationship between the informativeness of the incoming trade and that of the outgoing one. In particular, a very informative signal induces the market maker who receives it to approach either a very informed market maker or a completely uninformed one. Indeed, the value of δ is stronger for the first and third class.

This polarized reaction at the aggregate level suggests the existence of two main strategies. Market makers can either hide their information by trading with less informed market makers, or assess the quality of their information by approaching more informed market makers. The former would entail a negative δ, while the latter a positive one. At aggregate level this would show up as a bi-modal distribution with the values of $\delta' s$ particularly high for the very informed and very uninformed counterparts.

It is also worth noting how these results change in the proximity of the auction. The value of δ drops for the class of very informed counterparts and increases for the class of the least informed ones. This is in line with the previous findings and suggests that as the auction draws nearer, hiding behavior prevails over experimentation. In aggregate, market makers systematically react to the information contained in the orders they receive by attempting to hide it. However, this specification does not answer the question of whether the same market maker simultaneously plays both strategies, hiding and experimenting. Indeed, only the analysis at the dealer's level can address this issue.

7.2 Identification of Alternative Trading Strategies

Once we have ascertained the existence of a relationship between market makers' behavior and informativeness of incoming trade, we can proceed to identify the different strategies. To do this, we use an econometric approach that explicitly models market makers' decision process.

The starting point is the estimation of Equation (15), that is the reaction function of the market maker. The fact that the choice of the market maker is a non-trivial function of the other market makers' choices and characteristics makes the problem very involved. Given that each single market maker decides his reaction function on the basis of other market makers' perception of his degree of informativeness, we should control for the reaction of all the other market makers, estimating the cross elasticities of the reaction functions for all the pairs of market makers in the market. Clearly, this is computationally cumbersome and, even with the richness of a high frequency dataset, unfeasible.

We therefore use an approach in which we first define the possible alternative choices by grouping the market makers in classes according to homogenous characteristics. Then, we solve the endogeneity problem by projecting the choice space (that has a dimension equal to the number of existing groups) onto the space of the choice characteristics (that has the dimension equal to the much smaller set of characteristics in each group) (Berry, Levinsohn and Pakes 1995).

The choice space is defined on the basis of the tree of alternatives (Figure 1). The market maker can either operate only by changing the bid and ask quotes and/or withdraw from the market, or directly place orders with other market makers. If the market maker decides to place orders directly with other market makers, he has also to choose which other market maker he wants to approach.

Each market maker can choose to place the order with five different types of market makers: "smart market-timers", "market timers", "averages", "quasi-contrarians" and "contrarians".[11] The *smart market timers* are the dealers whom the market maker is confident (with confidence in excess of 90%) are able to successfully time the market, i.e., they buy before an increase in prices and sell before a reduction in prices. The *market timers* are the ones the market maker believes to be able to successfully time the market with confidence between 50 and 90%. The *averages* are the ones whom the market maker has low knowledge about (confidence level lower than 50%). The *contrarians* are the market makers whom the market makers is very confident (90% confidence level) follow contrarian strategies (sell before increase in prices and buy before a reduction in prices). Finally the *quasi-contrarians* are the market makers whom the market maker believes to

[11]It is worth noting that we have separated the market makers into 5 groups on the basis of the $(1-p)$ value of the coefficient γ_{ji}, while we have used the product of $(1-p)$ and γ_{ji} to identify the market makers in terms of degree of informativeness. The reason for this is that the degree of informativeness is potentially unbounded, while the value of $1-p$ is bounded by 1 and 0, allowing us to separate the market makers into 5 groups. The degree of informativeness takes into account not only the confidence in the degree of informativeness $(1-p)$, but also the impact on the market (γ_{ji}) of such a market maker. Therefore, it captures the "likely impact" on prices that trading with a particular market maker involves.

follow contrarian strategies with a confidence between 50% and 90%. The contrarians and the quasi-contrarians can be considered as intermediaries who have outside constraints inducing them to time the market in the wrong direction. One reason could be that they intermediate liquidity demand or that they have books with accumulated limit-orders.[12]

Contrarian and market timers can be considered as informed market makers who have different information. This implies that the decision of a market maker hit by a market timer to approach a contrarian as well as the decision of a market maker hit by a contrarian to hit a market timer can be interpreted as hiding. The reason being that the hit market maker is approaching a market maker who has information that is different from that held by the dealer who has placed the originating trade. Therefore, he expects him not to be able to make use of the additional information he is providing with his trade.

Every single transaction is a choice, and the frequency of the choice is given by the number of transactions during the specified time interval. Each alternative is simultaneously competing with the other alternatives at the same level of the tree (e.g., approaching a market maker who is well informed vs. approaching a market maker who is not informed) as well as with all the other alternatives (i.e., not placing any order directly with other market makers, but only changing the bid and ask quotes).

The market maker selects the alternative that guarantees him a payoff higher than that produced by the other alternatives. It can be shown (Berry 1994, Berry et al. 1995) that the reduced form can be expressed as:

$$\ln(s_{ji,t}) - \ln(s_{j0,t}) = \beta_0 + \psi \ln(s_{ji,t|endo}) + \beta_{EV} EV_{ji,t} + \beta_{\sigma P} \sigma^2_{k,t} + \mu_j + \eta_{ji,t}. \qquad (21)$$

(see Appendix B for a detailed derivation). This specification relates the choice of the *j-th* market maker to the degree of informativeness of the *i-th* market maker he chooses to deal with ($EV_{ji,t}$) and to some characteristics observable by the market maker, but not perceived by the econometrician (μ_j). Equation (21) is estimated bond by bond, but, for simplicity, we drop the subscript "k".

$s_{ji,t}$, $i = 1, ..., 5$ is the probability that the *j-th* market maker would select the *i-*

[12] Assume that the dealer has a set of orders to sell when the market reaches a certain level. He should execute the orders, even if he believes that the market is assumed to go up. This would give the appearance that the dealer is timing the market in the wrong direction.

th endogenous alternative. It is defined as the ratio between the orders that the *j-th* market maker places with the market makers belonging to the *i-th* group in the 10 minutes following the originating trade, and the total amount of trades (both endogenous and exogenous) that he deals with in the same interval.

$s_{j0,t}$ is the probability that the *j-th* market maker would select to go *exogenous*. It is defined as the ratio between the orders that the *j-th* market maker receives from other market makers in the 10 minutes following the originating order, and the total number of trades (both endogenous and exogenous) that he deals with during the same interval. Finally, $s_{ij,t|endo} = s_{ij,t}/\sum_{i=1}^{5} s_{ij,t}$ is the probability that the *j-th* market maker would select the *i-th endogenous* alternative, *conditional* on having decided to go endogenous. That is, it is the ratio between the orders the *j-th* market maker places with other market makers belonging to the *i-th* choice group in the 10 minutes following the originating order, and the total number of orders that, during the same interval, the *j-th* market maker places endogenously.

The stochastic term μ_j controls for the distribution of market makers' preferences and plays the role of "mean of the valuations that each market maker has of the other market makers." This includes things such as "club relationship" among particular groups, preferential treatments, and so on.

The coefficient ψ represents the degree of heterogeneity across alternative choices within the group. It ranges from zero to one. When it is equal to zero, the choices within the specific group are perceived as different from one another. When it is equal to one, the choices are perceived as close substitutes for one another (see Appendix B for a detailed derivation).

$EV_{ij,t}$ defines the characteristics of the counterparts the market maker is trading with. In particular, it captures the difference in the degree of informativeness between the market maker placing the originating order and the market maker whom the "hit" market maker approaches. To define this, we first calculate the product of the value of γ_j and $(1-p)$, where p is the probability value of the coefficient as defined in Equation (18). Then we calculate the difference between the average of the expected value of the degree of informativeness of the market makers of each group, and the expected informativeness of the dealer who is placing the originating order.

The model (21) is estimated for each market maker separately on the basis of transaction time. Then, the market makers are classified into three groups based on the nature of their response to informed trade (coefficient β_{EV}). A cross-validation technique is used to identify the classes of market makers, to group them and to test the stability of such a grouping. [13] Furthermore, in order to assess the stability of the results to a change in the market volatility, we estimate Equation (21) in two different volatility regimes (high and low volatility). "High volatility" periods are the days when the daily volatility exceeds the volatility over the previous 10 trading days. The results, reported in Table 5, Panel C, agree with the other ones (Table 5, panels A and B).

The results strongly support our hypotheses. In Table 5, Panel A, we report the results of the specification based on transaction time, estimated by grouping the market makers according to the institutional classification as well as to the trading-based one. There are different patterns of behavior among the classes of market makers. In general, *sneakies* try to hide their information. In order to do this, they direct their trade towards market makers less informed than the ones who have hit them. Therefore, if they are hit by market timers, they place orders with less smart market timers, averages and contrarians. Empirically, this corresponds to positive and strongly significant $\beta_{EV} = 90.10$. Also, if they are hit by contrarians they place orders with less contrarians, averages and market timers (estimate of $\beta_{EV} = -128.44$ is strongly significant, t-statistics is -8.76). That is, they always "go for the centre", towards the less informed (classes II, III and IV).

The *skeptics* behave in the opposite fashion, placing orders with market makers more informed than the ones they receive orders from. That is, if they are hit by market timers, they approach smarter market timers. Estimates in Table 5, Panel A, show that in that case $\beta_{EV} = -96.16$ with t-statistics -4.62. Alternatively, if skeptics are hit by contrarians, they approach even "more contrary" contrarians ($\beta_{EV} = 87.02$). Unlike the sneakies, they always go for the "wings", toward the extreme classes (I and V).

[13] In particular, we split the sample into odd and even days. Then we estimate Equation (21) in the odd days, we use the values of the estimated coefficients β_{EV} to identify the classes the market makers belong to and then group the market makers according to such a classification. Then, we use the sample period based on even days to estimate the value of the aggregated coefficients. In Table 5, Panels A, B and C we report the results estimated on whole period. Also, as a sensitivity analysis we run the same experiment using the even days to identify the dealers. The results agree with the ones reported.

The *sleepies* behave less strategically. They act only when they are sure about the informational content of the trade they receive, and do not experiment. Therefore, they do not go endogenous at all when they are hit by contrarians or averages, although they hide when hit by market timers.

In Table 6 we report some descriptive statistics about the three types of dealers. It appears that even if skeptics and sneakies represent a minority of the market makers (respectively 9% and 18% of all the market makers), they still are a significant fraction of the overall informed endogenous trading (respectively 34% and 24%). Also, if we rank all the market makers on the basis of their average daily trading volume, four out of the first five market makers are always either sneakies or skeptics.

If we pierce the veil and attempt to consider the corporate characteristics of the market makers, we find that the sneakies are mostly foreign banks and some highly specialized investment companies. The fact that foreign banks intermediate the investment in the Italian market of the large international institutional investors, would suggest that they have a better information set based on the knowledge of the flows. This would suggest higher informational advantage and stronger incentive to hide. The skeptics, instead, are medium-sized highly efficient banks. The relatively small size would justify high risk aversion or, in any case, higher cautiousness.[14]

It is interesting to note that when market makers are classified according to the institutional classification, both *specialists and ordinary market makers* generally behave like sneakies (Table 5, Panel B). This reflects a general tendency to try to hide information.

The analysis of *the degree of heterogeneity across alternative choices* that comes out of these results shows that, in general, the five alternative choices are perceived to be quite different. The degree of heterogeneity is rather high, with ψ close to the middle of the range (around 0.5). It is even higher for skeptics who have to approach more informed traders rather than less informed ones.

8 H4: Market Makers' Strategies and Market Volatility

In order to test whether different strategies imply different reactions to market volatility, we test the restrictions imposed by Equation (17). By using the specification 21), the

[14]Unfortunately no further investigation in greater detail is allowed by confidentialy requirements.

testable implications are:

$$\beta_{\sigma_P}^{skeptics} < 0 \text{ and } \beta_{\sigma_P}^{sneakies} > 0.$$

That is, the correlation between market volatility and informed endogenous trade is negative for the skeptics and positive for the sneakies.

The results, reported in Table 5, Panels A and B, show that this is indeed the case and that an increase in market volatility induces the skeptics to reduce their trading with more informed market makers and the sneakies to increase their trading with more informed market makers. All coefficients for sneakies (skeptics) are positive (negative) with four out of five significant at a 5% level.

An alternative specification is reported in Table 5, Panel C where we separate the sample in periods of high and low volatility. The testable implications of H4 can now be written as:

$$|\beta_{EV}^{high}| < |\beta_{EV}^{low}| \text{ for skeptics and } |\beta_{EV}^{high}| > |\beta_{EV}^{low}| \text{ for sneakies,}$$

where the indexes *high* and *low* refer to the two states of high and low volatility. The results show that in general those conditions are satisfied for relevant groups (I, II, IV and V).

9 Conclusions

We have analyzed market makers' decision to strategically experiment. We modelled such a decision as the result of a complex strategy involving the direct placement of orders with other market makers in the secondary market.

By using a unique dataset that traces market makers' behavior on the Italian Treasury bond market, we have shown that market makers actively learn from the market makers they are trading with. They use this knowledge to react strategically to the information content of the orders they receive, playing strategies that depend on the quality of this information. In particular, we have identified two main types of strategic reaction to the informational content of trade: "hiding" and "experimenting" and shown under which conditions experimentation is the preferred one.

These results open up a new and interesting avenue of research. In particular, if market makers react differently to the information they receive, their impact on market prices also differs. From this perspective, it may be possible to use market makers' reactions to information to explain otherwise puzzling evidence on asset prices, volume and volatility. Market efficiency and price reaction to trade can be better analyzed and explained in the context of market makers' strategic interaction.

A Market Maker's Problem

Proof of Proposition 1

Market makers observe a signal (ξ) and try to infer the value of θ. Let us assume that (θ, ξ) is a two-dimensional partially observable random process where ξ is the observable component, θ is the unobservable component and $\mathbf{E}$ is the set of possible values that the unobservable component (θ) can take. In particular, assume that the unobservable component follows:

$$d\xi_t = A_t(\theta_t, \xi)dt + B_t(\xi)dW_t$$

where W_t is a Wiener process. From Liptser and Shiryaev (1977, page 333) we know that the posterior probability of the state $\beta \in \mathbf{E}$ is:

$$\pi_\beta(t) = p_\beta(t) + \int_0^t \Re\pi_\beta(u)du + \int_0^t \pi_\beta(u)\frac{A_u(\beta,\xi) - \overline{A}_u(\xi)}{B_u(\xi)}d\overline{W}_u \tag{22}$$

where: $\Re\pi_\beta(u) = \sum_{\gamma\in\mathbf{E}} \vartheta_{\gamma\beta}(u)\pi_\gamma(u)$, $\overline{A}_u(\xi) = \sum_{\gamma\in\mathbf{E}} A_u(\gamma,\xi)\pi_\gamma(u)$ and $\overline{W} = (\overline{W}_t, \Im_t)$ is a Wiener process with: $\overline{W}_t = \int_0^t \frac{d\xi_u - \overline{A}_u(\xi)}{B_u(\xi)}$. Here $\Im_t$ is the information set available at time t. In our case, the unobservable component (θ) can take values a and b (that is $E = [\mu_H, \mu_L]$). The observable component is ξ. Applying Equation (22), we have:

$$\begin{aligned} d\pi_{\mu_H} &= (1-2\pi_{\mu_H})\vartheta dt + \\ &\quad \frac{\pi_{\mu_H}(1-\pi_{\mu_H})(\mu_H-\mu_L)}{\sigma_\xi^2}\left(\frac{ds}{s} - \left[\pi_{\mu_H}\mu_H + (1-\pi_{\mu_H})\mu_L\right]dt\right), \end{aligned}$$

If we define $\mu_{\pi_{\mu_H}} = (1-2\pi_{\mu_H})\vartheta$, $d\nu = \left(\frac{ds}{s} - \left[\pi_{\mu_H}\mu_H + (1-\pi_{\mu_H})\mu_L\right]dt\right)$ and $\Sigma = \left(\frac{\pi_{\mu_H}(1-\pi_{\mu_H})(\mu_H-\mu_L)}{\sigma_\xi^2}\right)$, we have:

$$d\pi_{\mu_H} = \mu_{\pi_{\mu_H}}dt + \Sigma d\nu.$$

B Econometric Specification

In this Appendix, we outline the derivation of a discrete choice model based on Berry (1994) and Berry et al. (1995). Let' s define the payoff of the *i-th* choice for the *j-th* market maker as:

$$u_i = x_i\beta_i + \mu_i + \varepsilon_i \tag{23}$$

where the subscript j for the market maker is omitted for simplicity. Equation (23) implies that the payoff of each individual market maker is a function of the characteristics of the other market makers he deals with (x_i) and some characteristics observable by the market maker, but not perceived by the econometrician (μ). A noise term ε_i is given by the distribution of market makers' preferences (risk aversion, etc.) around a mean value represented by μ. The *j-th* market maker selects the action that guarantees a payoff higher than that of the other alternatives, that is

$$u(x_i, \mu_i, \varepsilon_j, \theta_d) > u(x_k, \mu_k, \varepsilon_j, \theta_d) \text{ for each } k = 1, ..., i-1, i+1, ..., K,$$

where θ_d is the set of choices. The probability of choosing the *i-th* alternative over the others can be represented by:

$$s_j(\delta(x, \mu), x, \theta) = \int_{A_{j(\delta)}} f(\varepsilon, x, \theta_\varepsilon) d\varepsilon_k \tag{24}$$

where s_i is the probability that the *i-th* alternative is chosen in the market and δ is the mean payoff associated with choice of the *i-th* alternative. It is calculated by integration over the area $A_{i(\delta)}$, that is across all the possible choices.

We assume that the market maker has first to decide whether to go exogenous or endogenous and, in the latter case, which other market maker to approach. The set of endogenous choices is $k = 1, ..., i, ..., K \in endo$. We also assume that the preferences of the market makers ε_{ij} be i.i.d. with "extreme value" distribution function. We can therefore represent the probability of each choice as a function of the average value of its characteristics ($\delta_i = x_i\beta_i + \mu_i$). The probability of selecting the *i-th* alternative is:

$$s_i(\delta) = \frac{\exp(\delta_i)}{\sum_{k=0}^{N} \exp(\delta_k)} = s_{i|endo}(\delta) s_{endo}(\delta), \text{where } s_{i|endo}(\delta) = \frac{\exp(\frac{\delta_j}{1-\psi})}{\sum_{i \in endo} \exp(\frac{\delta_j}{1-\psi})} \tag{25}$$

represents the probability of choosing the *i-th* alternative once the decision of going endogenous has been taken, and

$$s_{endo}(\delta) = \frac{(\sum_{i \in endo} \exp(\frac{\delta_i}{1-\psi}))^{(1-\psi)}}{(\sum_{i \in endo} \exp(\frac{\delta_i}{1-\psi}))^{(1-\psi)} + \exp(\delta_{exo})} \tag{26}$$

represents the probability of going endogenous relative to the probability of going exogenous. The coefficient ψ represents the degree of heterogeneity across alternative choices within the group. It ranges from zero (when the choices within the specific group are perceived as different) to one (when the choices are perceived as close substitutes).

Given the existence of a unique mapping from the mean payoff to the probability of choosing one alternative (equation 24), we can invert this relationship so as to express the probability of choosing on alternative as a function of the mean payoff. By equalizing the probability derived from equation 24 to the actual choices directly observed on the market ($\widehat{s}_{i,t}$), we can derive the reaction functions of the market makers. In particular, for the *j-th* market maker selecting the *i-th* alternative:

$$\ln(s_{ji,t}) - \ln(s_{j0,t}) = \psi \ln(s_{ji,t|endo}) + \beta x_{ij,t} + \mu_j + \eta_{ij,t}. \tag{27}$$

C Robustness Checks

This Appendix describes the numerous robustness checks performed while testing the hypotheses of the paper. These results are available upon request from the authors.

C.1 H1: Informational content of trades

In addition to using the official and the trade-based classification of market makers, we also consider an alternative criterion, *separating market makers according to their volume of trading in the secondary market.* For each month, we calculate the trading volume of each single market maker in the market and then we group the market makers into quartiles on the basis of their total volume. The specialists always coincide with the biggest market makers, falling into the first quartile, while the ordinary market makers fall mostly into the second, and partly into the third quartile. Ordinary market makers belong partly to the third and mostly to the fourth quartile. Alternatively, we also group dealers separating them according to volume of trade on the secondary market and allocating them to *quartiles with equal number of dealers in each.* This results in having more than half of the total volume traded concentrated in the first quartile.

We also experiment with extending the reaction period to 30 minutes. That is, we consider all the trades (either exogenous or endogenous) enacted by the market maker in the next 30 minutes. The rationale in doing this is that the probability of receiving two consecutive orders with the same sign can be due to market makers' induced trade (exogenous trading), as well as to market makers' inability to move the bid-ask spread in time to avoid being "picked off" by other informed agents (Foucault, Roell and Sandas 1999) Extending the window allows us to discriminate against such hypothesis.

In the case where the market maker is picked off, the sign of the relationship should be negative and should not remain significant when the reaction window is extended from 5 to 30 minutes. The results show that exogenous trading is due to the decision to change the bid and ask prices posted by the market maker and not to pick-off. Furthermore, the fact that the relationship is stable when we extend the reaction window from 5 to 30 minutes suggests that the reaction is very unlikely to be due to lack of time for the market maker to change his bid and ask.

C.2 H2: Preliminary testing of informativeness of trades

C.2.1 Controlling for the role played by informed trade

We investigate the relationship between "informed incoming trade" and outgoing trade, by considering a linear specification where endogenous and exogenous trade are directly related to the informational content of trade:

$$Q^l_{jik,t} = \alpha + \beta T^{Inf}_{jik,t} + \varepsilon_{jik,t}. \tag{28}$$

$T^{Inf}_{jik,t} = \gamma_{ji} T_{jik,t}$ represents the "informative order" in the *k-th* bond received by the *j-th* market maker from the *i-th* dealer at time *t*. It proxies for the information contained in the trades and is constructed as the product of the trade that the *j-th* market maker has received in the specified time interval by the *i-th* dealer and his prior on his the degree of informativeness. $Q^l_{jik,t} = Q^{endo}_{jik,t}, Q^{exo}_{jik,t}$ represents the endogenous or exogenous trade of the *j-th* market maker in the 10 minutes following the originating trade. This specification should capture the part of market makers' reaction in addition to that otherwise determined by inventory rebalancing.

Sampling is based on transaction time. The analysis is carried out disaggregated at the level of individual market makers. The pairwise reactions from each class of market maker versus the other market makers are separately considered and are classified on the basis of the type of dealer who has placed the originating trade. To assess the robustness of the results to the change of the underlying distribution of the model, we also test them by running a bootstrapping procedure based on 10,000 resamplings.

The results, consistent with the ones reported in the text, show that in general the information-driven trades have higher power to explain endogenous trade than to explain exogenous trade. Indeed, the absolute value of the coefficients (β) and the high significance of their t-statistic show that ordinary market makers and specialists always react to informed trade by going endogenous. This holds both in the case of the institutional classification and n the case of the trading-based one.

C.2.2 Controlling for different definitions of variables

We experiment with different learning windows. In particular, we extend the learning period to the 25 previous days. The results agree qualitatively with those found using the 10 day learning interval: only the degree of significance drops, given the additional noise induced by the lengthening of the sample period.

Also, we redefine the learning interval around auction days. In particular, auction day-learning is defined on the previous 10 *auction* days, while non-auction day-learning is defined in the previous 10 *non-auction* days. The intuition is that, if in auction days market makers behave differently, we expect learning not to be the same in the two regimes and the prior on the degree of informativeness of specific market makers to diverge. The results agree with those based on a single learning matrix for the whole period.

C.2.3 Controlling for price momentum

We want to control for the possibility of a sort of "momentum" on prices. That is, the possibility that trade is more determined as a reaction to changes in prices than an autonomous decision of the market maker. We therefore estimate the following specification:

$$\Delta P_{k,t} = \gamma_{ji} T_{jik,t} + \delta \Delta P_{k,t-5} + \varepsilon_{jik,t} \tag{29}$$

where $\Delta P_{k,t-5}$ represents the change of prices in the past 5 minutes of the *k-th* bond. The results of the estimate seem to indicate that the trade of ordinary market makers is somewhat driven by momentum considerations, but in all the other aspects, the results agree with the ones reported in the text.

C.2.4 Controlling for inventory rebalancing

In order to control for inventory effects, we consider two alternative specifications. The first consists of testing explicitly the informational content of each trade, after having eliminated the residual effects due to inventory rebalancing. To do this, we first determine the component of the trade reaction of the market makers orthogonal to total trades ($\varepsilon_{jik,t}$), and then we see how much of it is explained by our measure of informed trade. In particular, we estimate:

$$Q^l_{jik,t} = \alpha + \gamma T_{jik,t} + \varepsilon_{jik,t}$$

where the variable $\varepsilon_{jik,t}$ is orthogonal to total trades. This is then regressed on informational trade according to:

$$\varepsilon_{jik,t} = \alpha + \beta T^{Inf}_{jik,t} + \eta_{jik,t} \tag{30}$$

It is worth noting that the additional explanatory power of $T^{Inf}_{jik,t}$ is due to the learning matrix that multiplies the part of total trades ($T^{Tot}_{jik,t}$) that are identified as "informed".[15]

A second specification directly separates the informational effect from the pure inventory one:

$$Q^{l}_{jik,t} = \alpha + \beta T^{Inf}_{jik,t} + \delta Inv_{jik,t} + \varepsilon_{jik,t}, \tag{31}$$

where $Inv_{jik,t}$ is the *i-th* market maker's inventory position at time t on the $k-th$ bond. In particular, for each market maker, we construct inventory ($Inv_{jik,t}$) as a time series based on market makers' purchases and sales over time. We use the definition of inventory of Hansch et al. (1998), calculating the standardized inventory

$$Inv_{jik,t} = \frac{Inv_{jik,t} - E_{Inv_{jik,t}}}{\sigma_{Inv_{jik,t}}},$$

where for each bond *k,* $E_{Inv_{jik,t}}$ and $\sigma_{Inv_{jik,t}}$are, respectively, the mean and the standard deviation of inventory over the sample. If market makers react to the information contained in the orders received, and if the informed trade has explanatory power additional to that of the inventory, there should be a positive correlation between information and market makers' trading reactions. A positive sign of β implies that market makers react to informed trade, while a positive δ is a sign of inventory-driven behavior. The results agree with the ones reported in the text.

C.2.5 Controlling for irregular spacing of observations

The use of transaction time has the benefit of capturing the varying degrees of significance that high and low volume periods have. However, the drawback of this approach is that it misses the effect due to the lapse of time when no transactions occur (Easley and O'Hara 1992, Diamond and Verrecchia 1987). To address this issue, we re-estimate some specifications using a GARCH structure where errors are modelled in the following way:

$$\varepsilon_{ik,t} = \rho \varepsilon_{ik,t-1} e^{\left(\frac{-\Delta t}{\tau}\right)} + \nu_{ik,t}.$$

where the time between two consecutive transactions (Δt) is explicitly accounted for as it interacts with the autoregressive structure of the variance. Also, ρ and τ are constants to be estimated together with the other parameters. The results agree with the ones reported in the text.

C.3 H3: Market makers' strategic reactions to information: hiding vs. experimentation

One possible problem in the estimation of the logit model is the quantification of the outside alternative (s_0), given that this should account for situations where there is pure exogenous trade, and where the market maker withdraws from the market. To cope with this, we define two alternative specifications: in the first one, we consider only the cases where there is at least one endogenous transaction in the 10 minutes following the

[15]These are the trades for which the learning matrix is defined. That is, the transaction has been originated by a dealer with a value of γ_{ij}, statistically significant at the 5% level.

originating trade.[16] In the second specification, we consider all the cases, assigning a weight of 100% to the choice to go exogenous if no transaction takes place in the 10 minutes following the originating transaction. Here, the observations are still defined in terms of the transaction times; that is, all the transactions the market maker is involved in during the 10 minutes following the incoming one. But, unlike the previous case, they are lumped together every 10 minutes on the basis of calendar time. This allows us to capture the decision to withdraw from the market. In this case we use clock time. The results agree with the ones reported in the text.

[16]We also looked at the case where the filter was to consider only the observations relative to situations where there were at least three transactions during the 10 minutes following the originating incoming order. Given that the results agree with those based on a one transaction filter, we do not report them. They are available upon request from the authors.

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Table 1. Sample Description

The sample consists of 1,393,437 transactions on the secondary market (Mercato Telematico dei titoli di Stato) in the period from September 29, 1994 to February 28, 1996. In Panel A we describe the bonds selected for the study. In Panel B we report volume (measured as number of transactions) broken down by the type of dealer. In Panel C we report average daily volume (measured as face value of the bonds traded times number of bonds). We consider overall volume, volume broken down on the basis of the type of intermediating market makers and volume broken down on the basis of both intermediating market maker and the type of the dealer who originates the trade. In Panel D we report a statistics of the transactions (defined in terms of face value) broken down by size.

Panel A: Types of Bonds

		Daily Volume, bln Lire	
Bond type	Transactions	Mean	Std. Dev.
Medium- and Long-term T. Bonds (BTP)	1,081,945	12,780	3,940
Financially Indexed Bonds (CCT)	301,306	3,710	3,600
Zero-coupon T-Notes (CTZ)	10,186	93	104

Panel B: Transaction Statistics of the Secondary Market

		Trade originating dealer		
Intermediating market maker	Total	Specialists	Ord. Market Makers	Ord. Dealer
Specialists	727,747	262,684	292,498	172,565
Ord. Market Makers	665,690	242,910	244,061	178,719
Total	1,393,437	505,594	536,559	351,284

Panel C: Daily Volume Statistics of Secondary Market (Bln Lire)

		Mean	Std. Dev.	Max
Overall		413.08	355.75	4175
Intermediating market maker				
Specialists		658.85	384.46	4175
Ord. Market Makers		283.57	258.50	2550
Intermediating market maker	**Originating dealer**			
Specialists	Specialists	239.05	142.35	1110
Specialists	Ord. Market Makers	266.51	173.88	1765
Specialists	Ord. Dealers	155.80	101.65	1370
Ord. Market Makers	Specialists	104.03	100.17	1350
Ord. Market Makers	Ord. Market Makers	106.53	105.35	850
Ord. Market Makers	Ord. Dealers	83.75	79.76	695

Panel D: Size Distribution of Transactions

Transaction size (Bln Lire)	Fraction of overall transactions
5	88.1%
10	10.1%
15	1.0%
≥20	0.8%

Table 2. Market makers' priors over other dealers' informativeness

We report the statistics of the learning coefficient γ_{ji} in the regression (18)

$$\Delta P_{k,t} = \gamma_{ji} T_{jik,t} + \varepsilon_{jik,t}$$

For each trading day we consider the pairwise relation of each dealer j versus all the other i dealers in previous ten trading days. $\Delta P_{k,t} = (P_{k,t+5} - P_{k,t})$ is the change in price $P_{k,t}$ in the 5 minutes following the originating transaction while γ_{ji} represents the degree of informativeness of the specific dealer. We define $T_{jik,t}$ as the signed volume received by the j-th market maker from the i-th dealer for the k-th bond at time t. For each single market maker a vector is defined that contains his estimated of the degree of informativeness of all the other dealers (γ_{ji}). We report t-statistics of the hypothesis $\gamma_{ji} = 0$. The reported γ_{ji} have been multiplied by 1000.

Panel A: Learning coefficient γ_{ji}, Institutional Classification of Dealers

		N	Mean	Std.Dev.	Min.	Max.	t-statistics
Overall		57,634	-1.30	2.525	-21.42	23.47	-123.6
Intermediating market maker	**Originating dealer**						
Specialist	Specialist	9,611	-1.31	1.37	-8.91	8.76	-94.1
Specialist	Market Maker	12,661	-1.27	2.29	-12.23	12.82	-62.3
Specialist	Ord. Dealer	4,027	-0.47	3.66	-18.65	19.90	-8.12
Market Maker	Specialist	13,062	-1.57	2.15	-13.55	10.73	-83.3
Market Maker	Market Maker	14,091	-1.51	2.66	-12.27	15.65	-67.5
Market Maker	Ord. Dealer	4,182	-0.62	3.87	-21.42	23.47	-10.3

Panel B: Learning coefficient γ_{ji}, Trading-based Classification of Dealers

Intermediating Market Maker	**Originating dealer**	N	Mean	Std.Dev.	Min.	Max.	t-statistics
Sleepy	Sleepy	29,134	-1.28	2.65	-21.42	23.47	-82.72
Sleepy	Skeptic	1,862	-0.55	2.80	-11.80	8.54	-8.53
Sleepy	Sneaky	9,530	-1.69	1.91	-12.23	15.65	-86.64
Skeptic	Sleepy	3,858	-1.61	2.38	-18.65	11.86	-41.95
Skeptic	Skeptic	187	-1.37	3.18	-9.82	10.88	-5.92
Skeptic	Sneaky	1,156	-1.82	1.33	-8.17	5.00	-46.82
Sneaky	Sleepy	9,006	-0.93	2.75	-12.42	12.45	-31.87
Sneaky	Skeptic	678	-0.24	2.85	-10.12	2.85	-2.16
Sneaky	Sneaky	2,223	-1.47	1.99	-11.00	7.29	-34.89

Table 3. A first test of strategic behavior

We report the results of the estimation of the model $s_{jk,t} = \alpha + \delta_I I_{ji,t} + \zeta\sigma^2_{k,t} + \theta d_j + \beta Q_{jik,t} + \varepsilon_{jik,t}$. Here $s_{jik,t}$ is the ratio between endogenous trade and total trade of the j-th dealer for the k-th bond in the 10 minutes following the originating trade (time t). We select only "informative" transactions, i.e. transactions that were originated by a dealer whom market maker is confident to be informed (p-value of γ exceeds 0.9). $Q_{jik,t}$ is the size of the order which the j-th dealer receives from i-th dealer for the k-th bond at time t. $I_{ji,t}$ represents a measure of the degree of informativeness of the i-th dealer as perceived by the j-th dealer. We consider two alternative measures of informativeness, the p-value of the coefficient γ_{ji}, and the product between the γ_{ji} and p-value. The first proxy represents the degree of accuracy of the signal (defined as 1 in the case of very significant variable and 0 in the case of insignificant one). The second proxies for the "expected" degree of informativeness of the dealer. $\sigma^2_{k,t}$ is the variance of the k-th bond in the 10 minutes before the originating transaction, while d_j is a dummy that controls for the dealer's idiosyncratic characteristics. The estimation is done using a consistent variance-covariance matrix generalized method of moments estimator. Lags of explanatory variables, overnight, one week, one-month, two-month and three month interest rates were used as instruments. The *t-statistics* of estimates are reported in brackets. p_H is the *p-value* of Hansen's overidentification criterion.

Panel A: Non-auction periods

Intermediating Market Maker	N	α	I_{EV}	I_{Pval}	$\sigma^2_{k,t}$	d_j	$Q_{jik,t}$	p_H
Overall	24,478	0.54	12.08	-	-3.41	-0.61	-.0013	0.33
		(71.70)	(2.82)	-	(-2.79)	(-1.83)	(-2.29)	
		-2.38	-	2.99	-2.76	-0.18	-.0061	0.33
		(-3.92)	-	(4.84)	(-2.95)	(-0.52)	(-3.19)	
Specialist	16,378	0.53	9.96	-	-2.79	-0.62	-.0006	0.26
		(56.31)	(2.01)	-	(-2.18)	(-1.49)	(-0.96)	
		-2.73	-	3.34	-2.58	11.1	-.0009	0.75
		(-3.95)	-	(4.75)	(-2.39)	2.62	(-1.52)	
Ordinary Market Maker	8,100	0.54	19.49	-	-4.80	-25.9	-.0028	0.30
		(46.39)	(3.21)	-	(-2.55)	(-4.33)	(-3.47)	
		-1.89	-	2.52	-2.71	-23.7	-.0035	0.93
		(-1.79)	-	(2.33)	-1.59	(-3.84)	(-4.31)	

Panel B: Auction periods

Intermediating Market Maker	N	α	I_{EV}	I_{Pval}	$\sigma^2_{k,t}$	d_j	$Q_{jik,t}$	p_H
Overall	3,709	0.55	7.59	-	-8.23	0.39	-.0035	0.22
		(30.40)	(0.72)	-	(-1.75)	(0.48)	(-2.44)	
		-2.13	-	2.54	-7.40	1.02	-.0041	0.98
		(-1.93)	-	(2.45)	(-1.73)	(1.18)	(-2.92)	
Specialist	1,200	0.56	-0.51	-	-11.59	2.01	-.0051	0.63
		(20.79)	(-0.03)	-	(-1.69)	(1.48)	(-2.55)	
		1.75	-	-1.21	-11.72	1.91	-0.005	0.99
		(1.02)	-	(-0.69)	(-1.86)	(1.30)	(-2.47)	
Ordinary Market Maker	2,509	0.52	27.84	-	-8.59	-5.08	-.0011	0.17
		(21.20)	(2.02)	-	(-1.63)	(-0.05)	(-0.75)	
		-4.11	-	4.75	-5.76	0.44	-.0030	0.99
		(-3.06)	-	(3.48)	(-1.17)	(0.42)	(-1.62)	

Table 4. Testing the existence of differential behavior

We reports the results of the estimation of:

$$s^{i}_{jk,t} = \alpha + \delta I_{ji,t} + \zeta\sigma^{2}_{k,t} + \theta d_{j} + \beta Q_{jik,t} + \varepsilon_{jik,t},$$

where $s^{i}_{jk,t}$ is the ratio between endogenous informed trade and total endogenous trade of the j-th dealer for the k-th bond in the 10 minutes following the originating trade (time t). Endogenous trade is split in three groups, depending on the degree of informativeness of the dealers whom the hit dealer approaches. We use the *p-value* of the γ_{ji} coefficient as defined in equation (18) to measure the accuracy of the signal of the dealer the "hit" market maker is placing his order with. $Q_{jik,t}$ is the size of the order which the *j-th* dealer receives by *i-th* dealer (the "originating dealer") for the *k-th* bond at time *t*. $I_{ji,t}$ represents a measure of the degree of informativeness of the *i-th* dealer as perceived by the *j-th* dealer. We report the results for two alternative measures of informativeness, the p-value of the coefficient γ_{ji}, and the product between the γ_{ji} and p-value. The first proxy represents the degree of accuracy of the signal (defined as 1 in the case of very significant variable and 0 in the case of insignificant one). The second proxies for the "expected" degree of informativeness of the dealer. $\sigma^{2}_{k,t}$ is a proxy of the volatility in the market at the time when the dealer receives the incoming order. It is defined as the variance of the *k-th* bond in the 10 minutes before the originating transaction, while d_j is a dummy that controls for the dealer's idiosyncratic characteristics. The estimation is done using a consistent variance-covariance matrix generalized method of moments estimator. Lags of explanatory variables, overnight, one week, one-month, two-month and three month interest rates were used as instruments. The *t-statistics* of estimates are reported in brackets. The *p-value* of Hansen's overidentification criterion (p_H) is also reported for each regression. FRA represents the accuracy of the informativeness of the Final Recipient, that is the dealer whom the "hit" market maker is placing his order with. It is the *p-value* of the γ_{ij} coefficient as defined in equation (18).

Panel A: Non-auction periods

Intermediating Market Maker	FRA	Variable						
		α	I_{EV}	I_{Pval}	$\sigma^2_{k,t}$	d_j	$Q_{jik,t}$	p_H
Overall	>0.9	0.60	72.24	-	-10.5	-9.63	-.00280	0.99
(N=24,478)		(42.26)	(8.21)	-	(-3.69)	(-12.10)	(-3.69)	
	0.5÷0.9	0.33	-12.96	-	9.42	3.44	-.00014	0.23
		(28.29)	(-1.99)	-	(4.60)	(7.36)	(-0.25)	
	<0.5	0.51	56.3	-	-3.89	-4.51	-.0031	0.12
		(29.97)	(5.73)	-	(-1.58)	(-5.64)	(-3.43)	
	>0.9	-5.64	-	6.47	0.07	-8.29	-.0049	0.42
		(-5.29)	-	(5.96)	(0.03)	(-13.3)	(-5.07)	
	0.5÷0.9	5.30	-	-5.09	8.73	2.67	.0002	0.99
		(5.99)	-	(-5.65)	(5.32)	(5.49)	(0.31)	
	<0.5	-10.66	-	11.47	0.96	-2.51	-.0041	0.10
		(-6.34)	-	(6.70)	0.40	-2.91	-3.63	
Specialists	>0.9	0.63	61.95	-	-12.63	-10.22	-.0030	0.19
(N=16,378)		(35.26)	(5.50)	-	(-4.24)	(-14.12)	(-3.39)	
	0.5÷0.9	0.32	-8.44	-	9.01	2.92	-.0002	0.27
		(22.99)	(-0.99)	-	(3.68)	(5.02)	(-0.26)	
	<0.5	0.54	25.6	-	-6.15	-5.12	-.0031	0.81
		(25.5)	(2.04)	-	(-1.63)	(-5.15)	(-3.14)	
	>0.9	-5.11	-	5.92	-3.21	-9.37	-.0041	0.71
		(-4.19)	-	(4.78)	(-1.28)	(-12.51)	(-4.09)	
	0.5÷0.9	1.50	-	-1.22	8.99	2.79	.0006	0.27
		(1.50)	-	(-1.19)	(4.30)	(4.66)	(0.09)	
	<0.5	-3.83	-	4.48	-3.76	-4.35	-.0037	0.40
		(-2.17)	-	(2.51)	(-1.09)	(-4.16)	(-3.21)	
Market Maker	>0.9	0.60	62.5	-	-2.51	-8.2	-.0034	0.99
N=8,100		(25.28)	(4.91)	-	(-0.58)	(-7.42)	(-2.13)	
	0.5÷0.9	0.34	-41.23	-	12.06	5.25	-.0004	0.37
		(19.48)	(-4.58)	-	(3.72)	(6.58)	(-0.37)	
	<0.5	0.52	70.04	-	0.787	-5.17	-.0035	0.22
		(20.81)	(5.48)	-	(0.21)	(-4.02)	(-2.11)	
	>0.9	-6.32	-	7.17	6.22	-6.78	-.0048	0.97
		(-3.27)	-	(3.63)	(1.80)	(-6.06)	(-3.57)	
	0.5÷0.9	7.19	-	-7.05	6.73	4.23	.0007	0.88
		(4.81)	-	(-4.63)	(2.40)	(5.14)	(0.61)	
	<0.5	-15.87	-	16.85	7.24	-3.34	-.0053	0.61
		(-5.07)	-	(5.27)	(1.71)	(-2.18)	(-2.11)	

Panel B: Auction periods

Intermediating Market Maker	FRA	Variable α	I_{EV}	I_{Pval}	$\sigma^2_{k,t}$	d_j	$Q_{jk,t}$	p_H
Overall	>0.9	0.67	59.53	-	-5.11	-8.94	-.0093	0.42
(N=3,709)		(20.34)	(2.93)	-	(-0.64)	(-6.61)	(-3.74)	
	0.5÷0.9	0.28	1.58	-	7.68	4.38	.0012	0.31
		(10.01)	(0.10)	-	(1.34)	(3.79)	(0.56)	
	<0.5	0.52	86.8	-	-1.71	-7.30	-.0061	0.32
		(13.38)	(3.10)	-	(-0.22)	(-4.34)	(-2.31)	
	>0.9	-5.77	-	6.63	1.98	-7.80	-.0120	0.44
		(-2.97)	-	(3.36)	(0.29)	(-5.28)	(-4.61)	
	0.5÷0.9	7.08	-	-6.91	10.77	3.16	.0011	0.18
		(3.86)	-	(-3.71)	(2.02)	(2.56)	(0.60)	
	<0.5	-12.59	-	13.46	-0.22	-4.39	-.0103	0.14
		(-3.16)	-	(3.31)	(-0.03)	(-1.96)	(-3.40)	
Specialists	>0.9	0.68	44.81	-	1.63	-5.03	-.0030	0.81
(N=1,200)		(17.01)	(1.93)	-	(0.19)	(-5.14)	(-3.14)	
	0.5÷0.9	0.32	-11.37	-	8.95	3.32	-.0007	0.48
		(9.41)	(-0.57)	-	(1.33)	(2.40)	(-0.33)	
	<0.5	0.52	70.82	-	1.63	-8.42	-.0077	0.24
		(9.55)	(2.05)	-	(0.19)	(-4.25)	(-2.31)	
	>0.9	-4.67	-	5.02	-1.01	-9.08	-.0111	0.23
		(-2.10)	-	(2.45)	(-0.13)	(-5.41)	(-3.41)	
	0.5÷0.9	5.46	-	-5.24	8.34	2.51	-.0003	0.31
		(2.83)	-	(-2.67)	(1.31)	(1.75)	(-0.12)	
	<0.5	-2.49	-	3.17	8.40	-8.22	-.0116	0.20
		(-0.65)	-	(2.01)	(1.14)	(-3.85)	(-3.60)	
Market Maker	>0.9	0.71	18.13	-	8.04	-7.5	-.0120	0.17
N=2,509		(6.06)	(0.72)	-	(0.52)	(-2.57)	(-3.36)	
	0.5÷0.9	0.28	-32.13	-	13.35	7.61	.0024	0.15
		(6.18)	(-1.24)	-	(1.32)	(3.54)	(0.86)	
	<0.5	0.41	129.81	-	-26.10	-6.20	-.0016	0.59
		(7.17)	(4.66)	-	(-1.67)	(-2.00)	(-0.36)	
	>0.9	-5.88	-	6.74	6.52	-4.55	-.0110	0.64
		(-1.69)	-	(1.91)	(0.45)	(-1.45)	(-3.02)	
	0.5÷0.9	4.40	-	-4.25	9.24	6.48	.0032	0.46
		(1.30)	-	(-1.23)	(1.11)	(2.97)	(1.18)	
	<0.5	-14.83	-	15.76	-12.9	-9.33	-.0084	0.32
		(-2.37)	-	(2.47)	(-0.50)	(-0.22)	(-1.51)	

Table 5. Hiding vs. experimentation: Transactions-based specification.

We report the results of the estimation of:

$$\ln(s_{ji,t}) - \ln(s_{j0,t}) = \beta_0 + \psi \ln(s_{it|endo}) + \beta_{EV} EV_{ji,t} + \beta_{\sigma P} \sigma^2_{k,t} + \mu_j + \eta_{jt}.$$

where, s_{it}, $i = 1, ..., 5$ is the probability that j-th market maker would select i-th *endogenous* alternative. s_{it} is defined as the ratio between the orders that the j-th market maker places with the market makers belonging to the i-th group in the 10 minutes following the originating trade, and the total amount of trades (both endogenous and exogenous) that he deals with in the same interval. s_{0t} is the probability that the j-th market maker would select exogenous alternative. It is defined as the ratio between the orders that the i-th market maker receives from other market makers in the 10 minutes following the originating order, and the total number of trades (both endogenous and exogenous) that he deals with during the same interval. $s_{it|endo} = s_{it} / \sum_{i=1}^{5} s_{it}$ is the probability of the i-th alternative conditional on having decided to go endogenous. That is, it is the ratio between the orders the j-th market maker places with other market makers belonging to the i-th choice group in the 10 minutes following the originating order, and the total number of orders that, during the same interval, the j-th market maker places. ψ represents the degree of heterogeneity across alternatives conditional on having chosen to go endogenous. $EV_{ji,t}$ is the average difference in expected value between outgoing endogenous trade and incoming trade over the 10 minute interval following the originating transaction, and σ_P is the standard deviation of prices of the bond in the 10 minutes after the transaction.

Each market maker can choose to place the order with “smart market-timers”, “market timers”, “averages”, “quasi-contrarians” and “contrarians”. The smart market timers are the dealers whom the market maker is confident (with confidence in excess of 90%) are able to successfully time the market, i.e., they buy before an increase in prices and sell before a reduction in prices. The market timers are the ones the market maker believes to be able to successfully time the market with confidence between 50 and 90%. The averages are the ones whom the market maker has low knowledge about (confidence level lower than 50%). The contrarians are the market makers whom the market makers is very confident (90% confidence level) follow contrarian strategies (sell before increase in prices and buy before a reduction in prices). Finally the quasi-contrarians are the market makers whom the market maker believes to follow contrarian strategies with a confidence between 50% and 90%. The model is estimated for each market maker separately on the basis of transaction time. Then the market makers are classified into three groups based on the nature of their response to informed trade (coefficient β_{EV}). The results of the estimation aggregated over those three groups are reported in Panel A. The results of the similar estimation aggregated over the official classification of dealers are reported in Panel B.

We report the results of estimation broken down by precision of incoming signal. Groups I to V correspond to the transactions initiated by “smart market timers,” “market timers,” “averages,” “quasi-contrarians” and “contrarians”, respectively. In Panel C the specification does not contain σ^2_P, but the estimations are performed separately for periods of ”high” and ”low” volatility σ^2_P. ”High” volatility periods are defined as the periods when the daily volatility exceeds daily volatility over the last 10 trading days. The estimation is done using a variance-covariance consistent generalized method of moments estimator. Lags of explanatory variables, learning coefficient of incoming trade γ and γ of the preceeding transaction are employed as instruments. *t-statistics* of estimates are reported in brackets. The *p-value* of Hansen’s overidentification criterion (p_H) is reported for each regression.

Table 5, continued.

Panel A: Trading-based Classification, Separation Over Precision of Signal

	I		II		III		IV		V	
Skeptic										
β_0	-0.41	(-19.56)	-0.37	(-24.28)	-0.41	(-19.40)	-0.31	(-8.95)	-0.32	(-4.75)
β_{EV}	-84.44	(-5.36)	-96.16	(-4.62)	54.28	(1.61)	87.02	(4.15)	36.34	(1.81)
$\beta_{\sigma P}$	-32.03	(-1.97)	-97.10	(-8.95)	-36.50	(-2.66)	-4.37	(-0.96)	-103.66	(-3.45)
ψ	0.32	(16.52)	0.35	(21.52)	0.38	(27.01)	0.44	(16.05)	0.39	(7.67)
p_H	0.24		0.79		0.47		0.89		0.10	
N	9,721		12,139		19,411		3,316		755	
Sleepy										
β_0	-0.28	(-34.97)	-0.27	(-44.24)	-0.24	(-39.34)	-0.29	(-24.1)	-0.31	(-13.49)
β_{EV}	33.17	(5.89)	31.73	(4.41)	14.73	(1.06)	-13.79	(-1.66)	-10.53	(-1.18)
$\beta_{\sigma P}$	-17.97	(-4.46)	-10.33	(-2.03)	-12.06	(-3.38)	-11.99	(-2.46)	-12.62	(-1.33)
ψ	0.47	(60.64)	0.46	(67.91)	0.45	(81.35)	0.43	(41.85)	0.39	(20.69)
p_H	0.27		0.98		0.99		0.52		0.39	
N	53,739		83,965		166,841		31,614		8,303	
Sneaky										
β_0	-0.37	(-24.68)	-0.36	(-31.98)	-0.31	(-33.91)	-0.49	(-25.12)	-0.56	(-17.75)
β_{EV}	66.11	(7.00)	90.10	(6.95)	-19.15	(-0.87)	-128.44	(-8.76)	-99.49	(-8.27)
$\beta_{\sigma P}$	24.25	(4.29)	14.48	(2.56)	10.26	(2.21)	32.63	(3.64)	5.51	(0.49)
ψ	0.52	(37.55)	0.53	(46.82)	0.54	(64.95)	0.59	(39.7)	0.60	(27.44)
p_H	0.14		0.18		0.10		0.59		0.27	
N	21,728		38,782		86,563		19,919		6,134	

Panel B: Institutional Classification, Separation Over Precision of Signal

	I		II		III		IV		V	
Specialist										
β_0	-0.34	(-40.44)	-0.34	(-50.40)	-0.32	(-43.15)	-0.42	(-30.13)	-0.51	(-20.00)
β_{EV}	24.70	(3.74)	44.79	(4.85)	11.94	(0.65)	-74.36	(-7.32)	-81.25	(-8.02)
$\beta_{\sigma P}$	-11.22	(-2.51)	-8.98	(-2.46)	0.29	(0.12)	4.29	(1.51)	16.22	(1.56)
ψ	0.47	(56.13)	0.48	(62.76)	0.49	(79.50)	0.52	(44.97)	0.51	(27.74)
p_H	0.47		0.24		0.99		0.64		0.09	
N	56,818		84,115		159,475		33,467		9,297	
Ord. Market Maker										
β_0	-0.26	(-22.60)	-0.26	(-30.37)	-0.22	(-32.98)	-0.28	(-19.12)	-0.28	(-10.01)
β_{EV}	29.41	(4.34)	25.69	(3.13)	13.24	(0.97)	-18.99	(-1.95)	-2.11	(-0.20)
$\beta_{\sigma P}$	-25.98	(-4.93)	-13.92	(-1.71)	-13.93	(-3.44)	-12.15	(-2.12)	-29.50	(-2.14)
ψ	0.46	(41.09)	0.47	(53.11)	0.44	(66.46)	0.46	(36.11)	0.46	(20.54)
p_H	0.44		0.96		0.18		0.86		0.20	
N	28,370		50,771		113,340		21,382		5,895	

Table 5, continued.

Panel C: Trading-based Classification, Separation Over Precision of Signal and High/Low Volatility Periods										
	I		**II**		**III**		**IV**		**V**	
σ_P^2	Low	High	Low	High	Low	High	Low	High	Low	High
Skeptic										
β_0	-0.41	-0.45	-0.45	-0.46	-0.41	-0.49	-0.44	-0.45	-0.32	-0.37
	(-22.92)	(-22.68)	(-31.30)	(-32.62)	(-20.01)	(-24.74)	(-13.16)	(-13.78)	(-4.75)	(-5.08)
β_{EV}	-98.45	-78.22	-138.21	-66.18	67.28	37.43	33.34	38.28	85.75	46.15
	(-6.09)	(-4.36)	(-5.25)	(-2.75)	(1.34)	(0.97)	(1.93)	(1.59)	(3.21)	(2.23)
ψ	0.50	0.46	0.51	0.51	0.55	0.53	0.54	0.57	0.50	0.51
	(34.37)	(30.10)	(37.68)	(38.60)	(48.63)	(47.65)	(22.49)	(25.71)	(11.17)	(10.27)
N	4,922	4,799	6,121	6,018	9,821	9,590	1,610	1,706	408	347
p_H	0.30	0.16	0.15	0.06	0.55	0.70	0.86	0.19	0.87	0.15
Sleepy										
β_0	-0.40	-0.43	-0.39	-0.41	-0.38	-0.40	-0.41	-0.42	-0.49	-0.49
	(-33.47)	(-35.19)	(-47.38)	(-50.07)	(-43.10)	(-44.80)	(-25.17)	(-25.47)	(-15.03)	(-14.15)
β_{EV}	25.62	19.56	9.52	3.42	0.75	29.54	7.69	5.55	-27.28	-13.47
	(3.22)	(2.37)	(0.86)	(0.34)	(0.04)	(1.50)	(0.60)	(0.44)	(-2.15)	(-1.11)
ψ	0.38	0.39	0.39	0.36	0.38	0.34	0.34	0.37	0.39	0.28
	(31.03)	(32.22)	(37.78)	(36.15)	(47.43)	(43.37)	(24.29)	(24.80)	(13.92)	(10.79)
N	26,478	27,261	41,105	42,860	84,623	82,218	15,759	15,855	3,969	4,334
p_H	0.28	0.23	0.83	0.84	0.99	0.90	0.98	0.75	0.84	0.22
Sneaky										
β_0	-0.60	-0.60	-0.57	-0.55	-0.49	-0.50	-0.67	-0.69	-0.66	-0.70
	(-21.02)	(-20.77)	(-28.84)	(-29.75)	(-32.68)	(-34.59)	(-21.08)	(-23.88)	(-14.17)	(-14.84)
β_{EV}	58.82	112.42	137.63	146.33	-18.90	-52.20	-152.35	-184.87	-81.20	-87.21
	(3.45)	(6.24)	(6.46)	(5.81)	(-0.54)	(-1.54)	(-5.54)	(-7.29)	(-4.80)	(-4.93)
ψ	0.45	0.50	0.49	0.52	0.49	0.53	0.52	0.60	0.64	0.53
	(19.12)	(21.85)	(26.10)	(28.34)	(38.66)	(41.28)	(23.47)	(27.49)	(20.51)	(18.33)
N	10,421	11,307	19,040	19,722	42,296	44,267	9,751	10,168	2,889	3,245
p_H	0.96	0.08	0.18	0.33	0.68	0.34	0.59	0.07	0.75	0.97

Table 6: Statistical description of sneakies, sleepies and skeptics

We report the summary statistics for the trading-based classification of the dealers. The fraction of the trade intermediated by a class of dealer is calculated as the percentage of transactions intermediated by dealers that belong to a particular group. We report the mean and standard deviation of daily trade per dealer. They are expressed at the face value of the bond traded. Ranking is obtained as follows: first dealers are sorted by volume intermediated. Then each dealer is ranked in descending order. The average ranking is calculated for each group. Volume-weighted ranking is calculated by using volume as weight.

$$R_V = \frac{\sum V_i r_i}{\sum V_i}.$$

Two rankings are reported. The first is based on the total trading volume the market makers intermediate, while the second is based only on the volume they generate (endogenous trade).

	Sleepy	**Sneaky**	**Skeptic**
Number of dealers in category	41	10	5
Share of overall exogenous trading (number of transactions)	61.2%	24.0%	14.8%
Daily Exogenous Trade, Mean (Bln Lire)	361.5	490.3	609.9
Daily Exogenous Trade, Std. Dev. (Bln Lire)	304.0	396.3	478.2
Average ranking over exogenous trade(out of 56)	31	11	14
Average volume-weighted ranking over exogenous trade (out of 56)	22	13	10
Daily Endogenous Trade,Mean (Bln Lire)	96.1	389.0	299.5
Daily Endogenous Trade, Std. Dev. (Bln Lire)	237.6	325.6	295.0
Average ranking over endogenous trade (out of 362)	27	21	22
Average volume-weighted ranking over endogenous trade (out of 362)	20	10	19
Share of overall endogenous trading (number of transactions)	70.2%	21.2%	8.6%
Share of informed endogenous trade in total endogenous trade	16.5%	24.2%	34.0%