EXPERIMENTATION IN FINANCIAL MARKETS*

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Individuals learn from experience and experiment to increase their information. We use a unique dataset on the Italian interdealer bond market to estimate the process of strategic experimentation. We provide a simple framework to analyze experimentation in the interdealer market and test it. We show that the information generated in the process of interdealer trading affects the incentive to experiment. We document that, upon receipt of an order, dealers deliberately engage in trade with other dealers either to exploit the information contained in the order they receive or, if they are uncertain about its quality, to assess it by actively experimenting with other dealers. We identify "hiding" and "experimenting" as main types of dealer strategies.

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Abstract

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"Experience has taught me that the way the market behaves is an excellent guide for an operator to follow...Ordinarily a man ought to be able to buy or sell a million bushels of wheat within a range of 1/4 cent. On this day when I sold the 250,000 bushels to test the market for timeliness, the price went down 1/4 cent. Then since the reaction did not definitely tell me all I wished to know, I sold another quarter of a million bushels. I noticed that it was taken in driblets...In addition to the homeopathic buying the price went down 1/4 cents on my selling. Now, I need not waste time pointing out that the way in which the market took my wheat and the disproportionate decline on my selling told me that there was no buying power there. ...Following the dictates of experience may possibly fool you, now and then. But not following them invariable makes an ass of you." (Lefevre 1994, p. 216).

1 Introduction

Learning from experience and experimentation are salient features of everyday life. Individuals take decisions on the basis of a limited information set, in most cases generated by experience. They may try to expand it by either collecting new information or simply assessing the quality of the one they already have. This experimentation process is costly both in terms of the direct cost of collection of information and in terms of the diversion of resources from more useful allocations.

Experimentation also entails a social dimension if the process of collecting information requires the interaction among individuals. It is likely that the information of the individual be based on repeated interactions with other agents. For example, an individual who receives information by an agent whom he deems, on the basis of previous interaction, to be informed will experiment less to improve his information, than somebody who receives information by a less reliable source. Moreover, experimentation itself may entail interaction. When this is the case, strategic issues arise. Indeed, while on the one hand interaction increases information, on the other hand, it also reveals part of the information available to the experimenter. There is therefore a delicate trade-off between the information the experimenter is willing to divulge and the one he thinks of collecting by experimenting.

While there exists an extensive literature that deals with strategic experimentation and learning from experience, there is basically no direct empirical evidence of it. The goal of this paper is to provide a first direct evidence of strategic experimentation, by using a unique experiment on the reaction to information in financial markets. We focus on the trade-off between costs and benefits by linking the incentive to experiment to the quality of the information the experimenter already has. This information is related to the experience that comes from repeated interaction with the other players in the market.

We consider the interdealer Treasury bond market. This allows us to use the richness of high-frequency data broken down at individual level in order to estimate the main implications of the theory of strategic experimentation. Interdealer trading contains an important informational dimension. The reaction of a dealer to an incoming order should depend not only on his inventory position and on the size of the order, but also on the identity of the dealer who has placed such an order. The prior on the ability and degree of informativeness of the trader placing the order should affect forecasts of future prices. For instance, if the order is placed by a trader who in the past has consistently bought before a rise in prices, the market maker can safely assume that prices will rise and should therefore act accordingly. As the number of active traders is rather small, repeated interactions do happen often. In such setting, reputation is important.

Trading allows the dealer to either directly exploit the information contained in the order he receives or, if uncertain about its quality, to assess it by actively experimenting with other dealers. The reaction of the other dealers he approaches should act as a reliability check on the quality of his information. We provide a simple model that captures this intuition and we bring it to the data.

We show that dealers actively learn from the dealers with whom they trade and classify them in terms of their degree of informativeness. We argue that this allows them to react strategically to the information content of the orders they receive, playing strategies that depend on the quality of the information received.

We identify two main types of strategic reaction to the informational content of trade: "hiding" and "experimenting". We show that some dealers selectively choose the other dealers with whom they place orders, in order to minimize the price impact of their trade. Others, however, choose their counterparts in order to learn the true quality of their information, by observing their reactions to the order posted. The choice of the type of strategy depends on dealers' priors about how well informed their trading counterparts are.

We use a unique high-frequency dataset on the Italian Treasury Bond market, disaggregated at dealer level. While the other two existing studies (Hansch, Naik, and Viswanathan (1998) and Reiss and Werner (1998)) on interdealer trading at the disaggregated level consider the equity market, we focus on the Treasury Bond market. This choice provides some additional benefits. First of all, the bond market has been only scarcely analyzed in the empirical literature, the main constraint being the lack of data. This is, to our knowledge, the first comprehensive study with data disaggregated at the individual level. Second, the bond market is a market where information is more about liquidity shocks and shifts in demand than about fundamentals. This makes it ideal to study dealers' reactions to order flows. Indeed, order flows can be used to proxy for information on liquidity shocks or changes in supply and demand functions, that is "semi-fundamental information"(Ito, Lyons, and Melvin (1998), Fleming and Remolona (1999)). Finally, the existence of regularly spaced informational events (Treasury bonds auctions) provides an ideal experiment to test for dealers' information-related strategies when the cost of acquiring information through experimentation changes.

1.1 Related Literature

There is an extensive theoretical literature that deals with experimentation. Moscarini and Smith (2000) and Keller and Rady (1999) consider experimentation in a single agent set-up, while Bolton and Harris (1999) and Cripps, Keller, and Rady (2002) analyze strategic experimentation in which individual players can learn from the experiments of others as well as their own. Bergemann and Valimaki (1997) and Bergemann and Valimaki (1996) consider strategic interaction in an oligopolistic market where players learn from their own market share. These models show that, when information obtained from an experiment is valuable to all players, individual players attempt to free ride on the experiment of others.

This dimension of learning based on active experimentation has gone largely unexplored in the market microstructure literature. In the interdealer market, analysis of dealer behavior has focussed primarily on what determines quotes, temporary inventory imbalances and the trade-off between the cost of stock-out and the cost of keeping inventory (Amihud and Mendelson (1980), Ho and Stoll (1981)). Alternatively, dealers are assumed to passively filter the information contained in the orders they receive and to react to it by setting quotes equal to their conditional expectations of the value of the asset (Kyle (1985), Kyle (1989), Madhavan and Smidt (1991), Dutta and Madhavan (1997)).

Even in the case in which strategic trading is analyzed (Holden and Subrahmanyam (1992), Spiegel and Subrahmanyam (1992),Vayanos (1999) and Vayanos (2001)), experimentation has rarely been properly considered. Only Leach and Madhavan (1993), and Leach and Madhavan (1992) suggest that experimentation might be an integral part of market maker' strategy. They propose a model of dealers' experimentation based on the optimal change of bid-ask quotes. But the role played by active trading - i.e. the decision of the dealer to place an order with another dealer - in experimentation has never been addressed and no empirical investigation has been carried out to test for dealers' experimentation and its relevance for financial markets.

More generally, the financial microstructure literature has not focused on the decision of the dealer about whether to engage in trade. The so-called "hot potato" theory (Lyons (1997)) assumes that dealers try to adjust undesired inventory imbalances by buying directly from or selling to other dealers. Dealers "pass orders along until they happen upon a dealer whose inventory discrepancy they neutralize" (Cao and Lyons (1999)). That is, as soon as a dealer is "hit" by an order, he attempts to neutralize its impact on his inventory positions by placing orders with other dealers. The process is assumed to be more or less mechanical, in the sense that the dealer does not optimally react to the informational content of the incoming trade.

However, given that each dealer has some priors on the degree of informativeness of the other dealers, dealer's reaction should be differentiated on the basis of the identity of who is placing the order. Moreover, the fact that dealers learn about other dealers' degrees of informativeness suggests strategic behavior. The empirical literature has mostly focussed on the inventory dimension of interdealer trading (Hansch, Naik, and Viswanathan (1998) and Reiss and Werner (1998)). It is important to note that our story does not compete directly with previous literature. Instead, we are proposing that the space of strategies can be richer than previous literature indicates.

The paper is organized as follows. In the next section we lay out a simple model.

In Section 3 we outline its empirically testable restrictions. In Section 4 we describe the market. Section 5 is devoted to the empirical estimation of the main testable restrictions. A brief conclusion follows.

2 The dealer's problem

We plan to show two points. The first is that *dealers learn from experience how to identify the informational content of the incoming trades and react differently, depending on it.* That is, the reaction to an order depends on the information that it contains. Such information is directly related to the identity of the dealers who are placing the orders. Each dealer has different priors on other dealers developed on the basis of past experience of trade with them. Different priors induce different reactions. An order from an informed dealer prompts a different reaction from an order from an uninformed one. Moreover, the order itself helps the dealer to update his priors on the hitter.[1]

The second point is that the dealer *exploits strategically the information contained in the order he receives. Experimentation is one of the strategies.*

The dealer selectively chooses his reaction on the basis of the informativeness of the incoming trade. If the dealer thinks that this is high and realizes that by trading he will impact the market in a way that can release it, he will try to exploit the information without revealing it. If, on the other hand, he is not confident about such information, he can use the reaction of the other dealers to his trade to assess its quality. In the former case the dealer will try to hide his information, in the latter one he will try to experiment to find out its true value.

On the basis of these considerations, we propose the following description of the dealer's decision process. A stylized representation is contained in Figure 1. Let us, for example, consider a dealer who receives an order at the ask. First, he assesses the quality of the information contained in the incoming order on the basis of his beliefs on the dealers with whom he has traded. The beliefs are updated daily by looking at price changes taking place after the trades.

[1] We also show that the reaction of the dealer is not necessarily an inventory one (those results are available upon request). Indeed, given that the dealer filters information from the trades he receives, he can react to trades not only to rebalance his inventory holdings, but also to exploit the information the bids bring him.

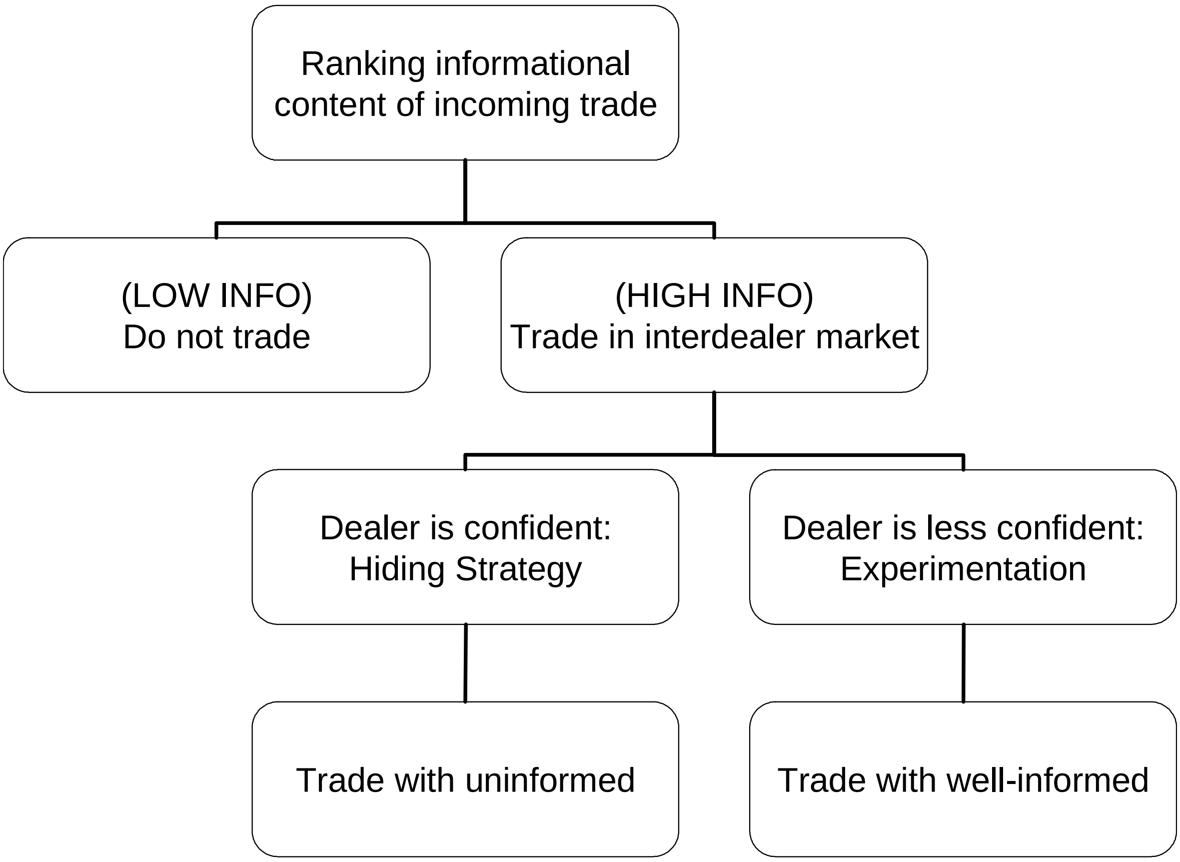

Figure 1: Dealer's choice tree

If the dealer deems the incoming trade informative enough, he will not divulge its informational content by changing quotes as this would immediately reveal the information to the whole market (Garbade, Pomrenze, and Silber (1979)). Given that, he risks being hit at the misaligned ask by another dealer who has acquired the same information, the decision not to alter the quotes is worth only if the incoming order is informative enough. Therefore, the starting point is to relate the informational content of the incoming trade to the reaction of the dealer. This hypothesis can be easily tested against the null hypothesis of no informational content of the standard inventory model (Ho and Stoll (1983)). However, to further investigate the issue we need to rely on a model that links the choice of dealer with whom to place an order explicitly to the informational dimension - i.e. the degree of informativeness of both the dealer placing the incoming trade and the dealer being approached. This type of analysis, if cast in a standard microstructure model, would immediately face limits in the "difficulty in working with models in which dealers are asymmetrically informed" (O'Hara (1995)).

We therefore take a different route. We resort to the economic literature on experimentation (Bergemann and Valimaki (1997), Bergemann and Valimaki (1996), Keller and Rady (1999), Bolton and Harris (1999), Moscarini and Smith (2000)). We use it to derive testable restrictions on dealer's behavior to bring to the data. This allows us to use the dealers' first order conditions as a base for the econometric estimation, without requiring us to solve the model for equilibrium.

On the basis of the considerations outlined above, we propose the following description of the dealer's decision-making process. We focus on the decision of the dealer who receives an order which he deems informative enough, and analyze his decision to engage in trade.[2]

We assume that the incoming trade acts as a signal (ξ) whose characteristics we will model later on. The dealer may react to it by trading with informed dealers (q^i), or uninformed ones (q^u). The total quantity traded can be expressed as: $q = (q^i + q^u)$.

[2] In the econometric estimation we will use a technique that allows us to control for the fact that the dealer may have changed the quotes and induced additional orders in that way.

Similarly to Kyle (1985) and Roell (1990), we define profits as[3]:

$$\Pi = q(v - p) = qs, \tag{1}$$

where s represents the spread between the true value of the asset (v) and the price at which the trade is executed (p).

The difference between market price and asset value is affected by the price impact of the dealer's trading: the more the dealer 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. Therefore, we assume that such a difference follows a stochastic process:

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

where z represents the main source of market uncertainty and λ^i and λ^u represent the impact on price of informed and uninformed trade respectively.[4] The dealer is fully aware that trading with more informed people has a stronger impact on prices than trading with less informed ones. Indeed, informed traders already have an information set which allows them to exploit the additional information. Therefore, $\lambda^i > \lambda^u$. For simplicity and with no loss of generality, we will standardize $\lambda^u = 0$.

The coefficient μ represents the difference between the value of the asset and its market price if the dealer did not trade. That is, it captures temporary misalignment between prices and asset values. It changes depending on market conditions. For simplicity we assume that his behavior is described by a Poisson process that can take up two values: high (μ_H) and low (μ_L). μ_H corresponds to the case where there is a strong possibility of profits to be made by arbitraging away the misalignment. μ_L corresponds to the case where the market price approximately reflects the asset's value. The probability transition

[3] We are focusing only on the decision of the dealer about which other dealer to approach. If we also account for the cost of not changing the bid-ask quotes, we could define s as the net profit, after netting out the cost of not changing the bid and ask quotes.

[4] Indeed the higher the spread, the less the dealers are 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 an informed market maker. We think that this specification better captures the picture of the higher the payoff, the greater the impatience of the dealer, and the weaker his desire to experiment.

matrix between time t and time $t + dt$ is:

$$\begin{array}{c|cc} & \mu_H & \mu_L \\ \hline \mu_H & 1 - \vartheta dt & \vartheta dt \\ \mu_L & \vartheta dt & 1 - \vartheta dt \end{array} \tag{3}$$

On the basis of these assumptions, we can write the law of motion of profits as:

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

2.1 Dealer's learning

Up to now we have assumed that the dealer 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 the market price. However, if the dealer is not fully informed, the decision problem changes drastically. Indeed, the dealer can now learn by observing the reaction of other dealers 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 dealer receives contains a signal (ξ) about μ. Such a signal is an unbiased predictor and follows the process:

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

where σ_ξ represents how noisy the signal is.

The dealer can reduce the noise by experimenting. That is, he can assess the quality of his signal by trading with other, potentially more informed, dealers. Therefore, the informativeness of the signal is positively related to the "informed trading" of the dealer: the more the dealer trades with informed dealers, the more he will increase the quality of his signal. His capacity to learn by placing orders with other dealers depends also on the overall market volatility (σ). The higher the market volatility, the less informative the reaction of the dealer with whom he trades. We can then define the law of motion of dealers' beliefs on μ as:

Proposition 1

The evolution of the posterior probability of the regime μ_H is:

$$d\pi_{\mu_H} = \mu_{\pi_{\mu_H}} dt + \frac{(1+q^i)}{\sigma^2} \Sigma d\nu, \tag{6}$$

where $\Sigma = \frac{\pi_{\mu_H}(1-\pi_{\mu_H})(\mu_H - \mu_L)}{\sigma_\xi}$ *and* $\mu_{\pi_{\mu_H}}$ *and* $d\nu$ *are defined in Appendix A.*

The term $\frac{(1+q^i)}{\sigma^2}\Sigma$ represents the flow value of information. It measures the incremental information that the dealer gains by posting an order with a more informed dealer. The greater this is, the more rapid the change in the posterior is. The dealer, after receiving an order, has a certain belief whose accuracy depends on the noise of the signal (σ_ξ). Therefore, Σ, which is negatively related to σ_ξ, represents the degree of informativeness of the incoming signal.

By placing orders with informed dealers (q^i) the dealer improves the accuracy of his beliefs. We can think of this as if the dealer were using the reaction of the informed dealers to his orders as a reliability check on the information he received with the incoming trade. The accuracy is a linear function of the amount traded with more informed dealers (q^i) and is negatively related to the market volatility (σ). Indeed, volatility makes it more difficult to interpret the reaction of the dealer with whom the order is placed, and therefore reduces the information value of experimentation.

2.2 The dealer's optimal trading strategy

We assume that the dealer is risk averse and endowed with a standard CRRA utility function $u(t, \Pi) = -e^{-\phi t}\frac{\Pi^{1-r}}{1-r}$, where r is the degree of risk aversion and ϕ is the intertemporal discount rate. The dealer solves the following problem:

$$Max_{q^i,q^u} \; E\left[\int_0^\infty [-e^{-\phi s} U(\Pi_s) ds]\right] \tag{7}$$

The Bellman equation of the dealer can be expressed as:

$$0 = J_\Pi (1 - \lambda^i q^i)(q^i + q^u)\hat{b} + \frac{1}{2} J_{\Pi\Pi}(q^i + q^u)^2 \sigma^2 + \frac{1}{2} J_{\pi\pi}(\frac{1+q^i}{\sigma^2}\Sigma)^2 + J_\pi \mu_\pi + J_t, \tag{8}$$

where $J_\Pi > 0$, $J_{\Pi\Pi} < 0$ and $J_t < 0$. $J_{\pi\pi}$ is the second derivative of the value function with respect to information and is always positive.[5] We see immediately that the dealer faces a trade-off between the gain from experimentation $(\frac{1}{2}J_{\pi\pi}(\frac{1+q^i}{\sigma^2}\Sigma)^2)$ and the cost incurred to experiment. This cost consists of the lower expected return due to the impact of the dealer's own trading on prices $(-J_\Pi \lambda^i q^i (q^i + q^u)\text{þ})$. The cost increases with the expected returns (þ) and with the impact of trading with informed dealers (λ^i). The higher the expected return and the stronger the price impact, the more costly it becomes to forego part of this by revealing information through experimentation. It is worth noticing that we are not explicitly focusing on inventory. In Appendix C we report the results of two different tests of the effect of inventory considerations. The results indicate that the trade originated by the dealer who was "hit" is not related to inventory consideration.

Solving the optimization problem defined in equation (7) we can define the optimal amount of experimentation.

Proposition 2

The optimal amount of trade with the informed dealers is:

$$q^i = \sigma \frac{(r-1)\text{þ}^2 \lambda^i \sigma^2 J + r\Sigma^2 J_{\pi\pi}}{(r-1)\left(\text{þ}\lambda^i \sigma\right)^2 J - r\Sigma^2 J_{\pi\pi}}.$$

This follows from the first order conditions applied on equation (8).

This model is, obviously, a reduced form of a more general equilibrium model. Nevertheless, it is still a useful tool in organizing our thoughts about dealers' behavior under a set of plausible assumptions. We will show in the next section that this simple model still produces powerful empirical restrictions that are supported by the data.

3 Empirical restrictions

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

[5] Indeed, the value of experimentation can only be positive as the dealer can always dispose of the additional information (Keller and Rady (1999), Bolton and Harris (1999)).

Hypothesis 1: The decision of the dealers to engage in trade is related to the degree of informativeness of the incoming trade.

If the dealers react to the signal contained in the incoming trade by placing orders directly with other dealers, we should find a relationship between the degree of informativeness of the incoming trade and the overall outgoing trades $(q^i + q^u)$. In particular, we have that:

$$q^{tot} = q^i + q^u = \frac{(1+\lambda^i)\mathbf{b}^2\Sigma^2 J_{\pi\pi}\Pi}{r\sigma\Sigma^2 J_{\pi\pi} - (r-1)\mathbf{b}^2\lambda_i^2\sigma^3 J}. \tag{9}$$

This implies that:

$$\frac{\partial(q^i + q^u)}{\partial\Sigma} \neq 0, \text{ unless } r = 1. \tag{10}$$

That is, in general we expect to find a relationship between the degree of informativeness of the incoming signal (i.e., Σ), and a dealer's decision to trade. This relationship is a function of the degree of risk aversion of the dealer. If he is very risk averse (more risk averse than a logarithmic, i.e. $r > 1$), the increase in the informational content of the incoming trade will induce him to trade less. On the contrary, if he is not very risk averse (less risk averse than a logarithmic, i.e. $r < 1$), the increase in the informational content of the incoming trade will induce him to trade more. That is,

$$\frac{\partial(q^i + q^u)}{\partial\Sigma} < 0 \text{ if } r > 1 \text{ and } \frac{\partial(q^i + q^u)}{\partial\Sigma} > 0 \text{ if } r < 1. \tag{11}$$

Only in the case where the dealer is endowed with a logarithmic utility function would there not be any relationship. Indeed, this would correspond to the case where learning uncertainty and estimation uncertainty exactly offset each other. The dealer would not hedge informational uncertainty, and therefore would not trade. It is interesting to notice that the behavior of the dealer resembles that of the standard investor in a portfolio model, where trading represents the decision to invest in the risky asset and provides the dealer with the way of hedging his risk (Brennan (1998), Brennan and Xia (1998), Xia (2001)).

The empirical consequence is that there should be a relationship between the decision of the dealer to place orders with other dealers and the degree of informativeness of the incoming trade. This provides the alternative to the inventory models which assume that the dealer only wants to rebalance his inventory and does not expect any correlation between trading and the information of the incoming trade. Indeed, he can simply change the bid and ask quotes. Trading, however, also presents the dealer with the opportunity to exploit his information. This general hypothesis should hold at the aggregate level, before a disaggregation of dealers depending on their degree of risk aversion. It implies:

$$H_0 : corr(q^i + q^u, \Sigma) = 0 \text{ and } H_A : corr(q^i + q^u, \Sigma) \neq 0. \tag{12}$$

Hypothesis 2: Dealers strategically select the other dealers with whom they place their orders either to hide their information ("hiding") or to increase it ("experimentation").

If order flows are informative, and dealers react strategically to these, part of a dealer's strategy would be the selective choice of trading partners. A dealer reacting to information contained in an incoming order has to decide how to use the information. If he is confident about its quality, he can try to "hide" this information and exploit it by trading with a dealer less informed than the one who has hit him. This would allow him to reduce the impact of his trade on prices. Alternatively, the dealer may want to increase his informativeness and "experiment". That is, he would test the quality of the information by assessing other dealers' reactions to his trade. In this case, he would place more orders with the more informed dealers than with the less informed ones. We can therefore define two types of strategies: hiding and experimenting.

We can relate the decision to place an order with informed dealers to the degree of informativeness of the dealer placing the order - i.e. to the informational content of trade or Σ. In particular, we have that[6]:

$$\frac{\partial q^i}{\partial \Sigma} = \frac{2\sigma^2\Sigma(r-1)r\widehat{\mu}^2\lambda^i(1+\lambda^i)JJ_{\pi\pi}}{\left[(r-1)\left(\widehat{\mu}\lambda^i\sigma\right)^2 J - r\Sigma^2 J_{\pi\pi}\right]^2}. \tag{13}$$

This implies that:

$$\frac{\partial q^i}{\partial \Sigma} > 0 \text{ if } r > 1 \text{ and } \frac{\partial q^i}{\partial \Sigma} < 0 \text{ if } r < 1. \tag{14}$$

That is, depending on the degree of risk aversion (r), dealers can be divided into two

[6] The same can be said for the share of informed trade in overall dealer's originated trade $\frac{\partial\left(\frac{q^i}{q^i+q^u}\right)}{\partial\Sigma} = \frac{2\sigma^4(r-1)\widehat{\mu}\lambda_i J}{(1+\lambda_i)\Sigma^3 J_{\pi\pi}\Pi}$.

groups which we would call "skeptics" and "sneakies". Skeptics place their trade with informed counterparts while sneakies place their orders with less informed ones. The intuition is that the former try to learn by hitting more informed dealers, 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 try to hide their information to exploit it better. Empirically this implies:

$$H_0 : corr(q^i, \Sigma) = 0 \text{ and } H_A : corr(q^i, \Sigma) > 0 \text{ for a skeptic,} \tag{15}$$

and

$$H_0 : corr(q^i, \Sigma) = 0 \text{ and } H_A : corr(q^i, \Sigma) < 0 \text{ for a sneaky.} \tag{16}$$

That is, 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 dealers with whom the hit dealer places an order. In the case of experimenting, on the contrary, a positive relationship is predicted.

Hypothesis 3: Dealers' strategic behavior on the secondary market should change when the costs and benefits of experimentation change. In particular, if both the costs and benefits are greater, there will be an increase in both experimentation and hiding:

The strategic behavior of the dealer should change when some informational event modifies the cost of trading (λ^i). In particular, we have that:

$$\frac{\partial \frac{\partial (q^i)}{\partial \Sigma}}{\partial \lambda_i} = -\frac{2(r-1)r\sigma^2\Sigma\hat{}^2 J J_{\pi\pi}[(3+2\lambda^i)\left(\lambda^i\hat{\sigma}\right)^2 J(r-1) + J_{\pi\pi}(1+2\lambda^i)r\Sigma^2]}{\left[(r-1)\left(\lambda^i\hat{\sigma}\right)^2 J - rJ_{\pi\pi}\Sigma^2\right]^3}. \tag{17}$$

That is, the relationship between the decision to trade and the degree of informativeness of the incoming trade is a function of both the level of the quality of the incoming signal (Σ) and the dealer's attitude towards risk. When the quality of information is sufficiently high:

$$\frac{\partial \frac{\partial q^i}{\partial \Sigma}}{\partial \lambda^i} > 0 \text{ if } r > 1 \text{ while } \frac{\partial \frac{\partial q^i}{\partial \Sigma}}{\partial \lambda^i} < 0 \text{ if } r < 1. \tag{18}$$

That is, only the very risk averse dealer will experiment, while the less risk averse will want to hide his information and trade upon it. Therefore, the former will increase informed trade, while the latter will reduce it. On the contrary, if Σ is sufficiently low:

$$\frac{\partial \frac{\partial q^i}{\partial \Sigma}}{\partial \lambda^i} < 0 \text{ if } r > 1 \text{ while } \frac{\partial \frac{\partial q^i}{\partial \Sigma}}{\partial \lambda^i} > 0 \text{ if } r < 1. \tag{19}$$

That is, if the informational content of the incoming trade is particularly low, the more risk averse dealer will not experiment, while the less risk averse dealers will do so. Therefore, if we are able to identify an event where the cost of experimentation (λ^i) changes, we can use the following testable restrictions. In the case where the degree of informativeness of the incoming signal (Σ) is high, for the sneakies we have:

$$\begin{aligned} H_0 &: corr(q^i, \Sigma)_{high\ \lambda^i} - corr(q^i, \Sigma)_{low\ \lambda^i} = 0, \\ H_A &: corr(q^i, \Sigma)_{high\ \lambda^i} - corr(q^i, \Sigma)_{low\ \lambda^i} < 0, \end{aligned} \tag{20}$$

while for the skeptics we have:

$$\begin{aligned} H_0 &: corr(q^i, \Sigma)_{high\ \lambda^i} - corr(q^i, \Sigma)_{low\ \lambda^i} = 0, \\ H_A &: corr(q^i, \Sigma)_{high\ \lambda^i} - corr(q^i, \Sigma)_{low\ \lambda^i} > 0. \end{aligned} \tag{21}$$

We will see in the empirical section that in the Treasury Bond market such an event exists and occurs at regular intervals, the auctions of Treasury Bonds.

Hypothesis 4: Dealers' reaction to market volatility σ depends on the strategy they play. An increase in volatility reduces the incentive to experiment and increases the incentive to hide.

In terms of the relationship to market volatility, the two classes of dealers display opposite behaviors. In particular, we have that[7]:

$$\frac{\partial q^i}{\partial \sigma} = \frac{(r-1)r\hat{\mu}^2\lambda^i(1+\lambda^i)2\sigma\Sigma^2 J J_{\pi\pi}}{\left[(r-1)\left(\hat{\mu}\lambda^i\sigma\right)^2 J - r\Sigma^2 J_{\pi\pi}\right]^2}, \tag{22}$$

[7] The same can be said for the share of informed trade in overall dealer's originated trade $\frac{\partial\left(\frac{q^i}{q^i+q^u}\right)}{\partial\sigma} = -2\frac{2\sigma^3(r-1)\hat{\mu}^2\lambda_i J + r\sigma\Sigma^2 J_{\pi\pi}}{(1+\lambda_i)\hat{\mu}\Sigma^2 J_{\pi\pi}\Pi}$.

This implies that:

$$\frac{\partial q^i}{\partial \sigma} < 0 \text{ if } r \text{ is high and } \frac{\partial q^i}{\partial \sigma} > 0 \text{ if } r \text{ is low.} \qquad (23)$$

that is, higher uncertainty in the market will have 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 engage in trade. The opposite is true for the sneakies who, being less risk averse, use the opportunity provided by higher volatility to trade without disclosing too much information. This allows them to engage in trade more. Empirically this implies:

$$H_0 : corr(q^i, \sigma) = 0 \text{ and } H_A : corr(q^i, \sigma) < 0 \text{ for a skeptic,} \qquad (24)$$

and

$$H_0 : corr(q^i, \sigma) = 0 \text{ and } H_A : corr(q^i, \sigma) > 0 \text{ for a sneaky.} \qquad (25)$$

4 The Market and the Dataset

We focus on the Italian Treasury Bond market in 1994-1996 period. In that period in Italy, there were three main types of traded bonds: Treasury Notes, Treasury Bonds and financially indexed bonds. Treasury Bonds (Buoni del tesoro Poliennali, or BTP) are long-term coupon bonds. Financially indexed bonds (Certificati di Credito del tesoro or CCT) are long term coupon bonds indexed to short-term Treasury Bills. Treasury Notes (Certificati del Tesoro a Zero Coupon, or CTZ) are 2-year zero-coupon bonds.

Since 1994, bonds have been traded both on the Milan Stock Exchange and on an inter-dealer based Treasury Bond Market (Mercato Telematico dei titoli di Stato, MTS). The overwhelming majority of trade in Treasury Bonds takes place on the latter market (Banca D'Italia (1995)). In 1994-1996 the number of bonds traded on the Stock Exchange was extremely limited and prices reflected the ones determined in the MTS. The MTS market is a screen-based system, operating between 9.00 a.m. and 5.00 p.m. (see Banca D'Italia (1994)). We report the descriptive statistics for our sample period in Panel A of Table 1.

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 permitted to act as dealers. Ordinary dealers may only place orders with market makers, and cannot post bid and ask prices. Market makers are dealers who commit themselves to continuously post bid and ask prices. They may place orders with other market makers. Specialists are market makers who must trade a minimum percentage of each type of bond on the secondary market and must purchase a minimum percentage of the bonds being auctioned off at each auction[8]. 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. For simplicity we will use the term *dealer* to define ordinary dealers, market makers and specialists. We report the descriptive statistics disaggregated over dealer type in Panels B and C of Table 1.

Each trader (ordinary dealer, ordinary market maker, primary dealer) has access to a screen where he can observe the bid and ask prices dealers (both specialists and ordinary market makers) post and the maximum number of bonds they commit themselves to trade (depth).[9]

Market makers are not anonymous *ex ante*. That is, the name of the market maker appear on the screen next to the bid and ask prices he posting.[10] Each dealer knows the identity only of the counterpart with whom he is trading, while no other market participant 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. However, unlike Nasdaq, orders are executed only at the bid and ask. There is no possibility of negotiating prices within quotes. The transaction takes place only at the posted price.

Given that each dealer observes the orders posted with him but not the ones posted with other dealers, each order changes the information set of the dealer in a way different from the other dealers who can observe only the fact that an order has been posted, but do not know its size or the identity of the trader who has placed it.

When it is executed, the name of the dealer “hit” blinks, signalling to the market that

[8]Specialists should maintain 3% market share in the primary markets and 1.5% share on MTS. Ordinary market makers should maintain a minimum share of 0.5% on MTS.

[9]All the dealers who post quotes have the obligation to trade at the quotes he posts, regardless of whether the quotes are away from the best bid and ask.

[10]Quotes became anonymous later, in June of 1997. From this time onward, all quotes at the same price posted by different market makers were aggregated, leading to an aggregate market depth associated with each outstanding quote. For an analysis of 1997 changes, see Scalia and Vacca (1999).

he is trading and listing the price at which the trade takes place. 88.1% of transactions are of standard 5 billion lira size, another 10.1% are of two standard size. Orders in excess of three standard size are extremely rare (less than 0.8% of transactions). This is despite the fact that the posted depth always allows dealers to trade significantly larger quantities[11].

As in 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.

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.

The primary Treasury bond market is based on uniform type auctions. A uniform cut-off price apply to all the winning bidders. At the beginning of the year the Treasury announces the schedule of the auctions, and then, one week prior to each auction, the Treasury announces the number of bonds that will be auctioned off in that specific auction. Dealers submit their demand schedules through a computerized telematic system (Rete Nazionale Interbancaria, R.N.I.) before 1 p.m. on the auction day. The official results are communicated to the market in the afternoon and include the quantities bid, the number allocated and the allotment price. There are two relevant moments during the day of the auction: the official auction deadline at 1 p.m. (*morning*) and the moment (*afternoon*) in which the Treasury announces the results of the auction. The Treasury announces the auction price, the total volume demanded and the total volume allotted. The auction takes place between 9 a.m. and 1 p.m.

[11] While we lack the systematic data on market depth, the anecdotal evidences are that in this period the normal depth was posted in 10-20 standard trade size range (50-100 bln. Lire).

To increase the depth of the market, the Treasury organizes re-openings whereby the same type of bond is issued repeatedly, with the same characteristics of the previously issued batches of the same bond traded in the secondary market. Accrued interest, residual life and tax treatment are designed in a way that the new batch of the bond is perfectly identical in value to the ones already issued. Given that bonds are traded on the secondary market immediately following the first issue, there is no need for a when-issued market. Re-openings represent more than 85% of the total auctions.

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

The sample has been divided into "days before the auction" and "all other days". The estimates for "days before the auction" [12] are made only for the bonds that are auctioned the next day. We did not consider the effects of macroeconomic announcements on trading due to the fact that during this period ("Convergence to Euro" period) the number of non-Italian events and macroeconomic announcements (German, French, Spanish, UK, etc.) were of higher significance than the announcements of Ministry of Finance or Bank of Italy.

5 Empirical testing

Before proceeding with the empirical tests of the existence of the informational content of trade and dealers' reaction to it, it is worth stressing that a motive for trade we want to control for is inventory-rebalancing. In order to properly control for it, we re-estimate the main equations that follow by including dealers' inventory. The results do not differ from the ones reported and are omitted due to space constraint.

[12] 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.

5.1 H1: Trade and information

5.1.1 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. Each dealer learns about the other dealers 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 dealer to update continuously his priors on the degree of informativeness of the other dealers 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 dealers' 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. For each dealer *j,* we consider *all* the orders received in the previous 10 days by the other i dealers. Each order is paired with the change in prices that takes place, on the same *kth* bond, in the following 5 minutes. This defines, for each dealer *j*, i pairs of vectors ΔP_k and Q_{jik}. We then estimate the auxiliary regression:

$$\Delta P_k = \gamma_{ji} Q_{jik} + \varepsilon_{jik}. \tag{26}$$

This is run in a pairwise relation versus all the other i dealers for each individual bond k and *on transaction time.* That is, each regression has as many observations as the number of trades that the *jth* dealer receives in the previous 10 days. We define Q_{jik} as the (signed) order received by the *jth* dealer from the *ith* dealer for the *kth* bond. ΔP_k is the change in the price of the *kth* bond in the 5 minutes following the receipt of such an order.[13] To assess the robustness of the results, we also experiment with different time

[13] $\Delta P_k = (P_{k,+5} - P_k)$ represents the change in price of the *kth* bond in the market, *regardless* of the identity of the dealers who are part of it. That is, it is not constructed by only taking the price for the *ith* dealer's transactions. We use actual prices in the next 5 minutes. So for P_{+5} to be defined, there should be a transaction in the same bond in such an interval. If there are many transactions, the last one within the interval is used. In the case no transaction exists, $P_{+5} = P$. To avoid problems due to thin trading, we consider only the regressions with at least 5 trades. We also experiment with different window length,

windows. The results are consistent with the ones reported.

This regression is estimated *for each dealer at the beginning of each day using 10-days window (from t-10 to t-1).* It is important to stress that for each day γ_{ji} is estimated using only past trades. A 10-day window has been chosen as an optimal trade-off between the accuracy of the estimation and the time-varying dimension of the estimate due to short-lived information.[14] Given the lack of availability of quotes, we follow Madhavan, Richardson, and Roomans (1997) and use the actual transaction prices and not mid-quotes. The presence of bid-ask bounces in the returns would induce negative serial correlation that would make it more difficult to detect information effects. This makes our tests more conservative. However, it is worth noting that the fact that there are several transactions in the 5 minute interval (the median number of transactions is 24), partially alleviates the problem.

Given that each dealer observes the orders posted with him but not the ones posted with other dealers, the coefficient γ_{ji} represents the informativeness of the specific *ith* dealer who is placing the order, as perceived by the *jth* dealer who receives it. 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, and the greater the informational content of the order received by the dealer.[15] A positive value of γ_{ji} means that the *ith* dealer has consistently bought (sold) from the *jth* dealer before an increase (decrease) in prices. [16]

This approach allows us to have, for each dealer, a vector of $\gamma_{ji}s$ corresponding to the estimated parameters of each *jth* dealer vis-a-vis the other i dealers. This lets us identify and construct classes of dealers on the basis of past interactions with other dealers and

considering 2 and 10 minutes intervals. Qualitatively those estimates are similar, but in 2-minutes one the number of observations with non-zero changes in prices are significantly smaller.

[14] We choose 10 days because they represent 2 full trading weeks and we expect that after such a period the short-lived information of the particular dealer already got impounded into prices. However, given that this is rule of thumb, we also experimented with different windows, including and excluding the days of the auction. The results are in line with the ones presented and are available upon request from the authors.

[15] To avoid problems due to thin trading, we consider only the regressions with at least 5 trades.

[16] The consistent positive sign suggests that we are not dealing with a phenomenon of price reversion. Also, it is worth noticing that we are not estimating an effective bid-ask spread as in Huang and Stoll (1997). Indeed, the interval we consider is wide enough to many transactions and by construction at least 5. Also, we do not rule out negative $\gamma's$. These may correspond to the situation when the dealer has a limit order to sell when the price reaches a certain level. We will discuss this type of behavior later in the text.

then to test their behavior *out-of-sample*.

In Table 2, Panels A and B, we report the results of the estimation of equation (26). 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 (ordinary market maker) is about 0.65 bp (0.75 bp) for the transactions originated by the dealer on whom the market maker has an informed prior (statistically significant γ_{ji}) and about 0.18 bp (0.24 bp) for all trades.

The dealers who are perceived as being more informed, both in terms of value of the 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 worth noting 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 (26) is capturing *only the temporary informational advantage that is related to "semi-fundamental information" like order flows or liquidity shocks* (Ito, Lyons, and Melvin (1998), Fleming and Remolona (1999)). It is unlikely that they reflect any long-term trading relationship between different dealers.

5.1.2 First test of strategic behavior

We can now test how this informational content is related to dealer's behavior. We consider a linear specification where a dealer's trade is directly related to the informational content of the incoming trade. We test the following specification:

$$P_{jk} = \alpha + \beta I_{ji} + \delta Q_{jik} + \zeta \sigma_k^2 + \theta d_j + \varepsilon_{jik}, \tag{27}$$

where P_{jk} is the ratio between the all trades the *jth* dealer places in the *kth* bond in 10 minutes following the originating trade and the total trade he executes in the *kth* bond during the same time period (i.e., the orders he places directly with other dealers as well as the orders he receives). It can be interpreted as the probability of placing orders in the *kth* bond in the 10 minutes following the originating trade. The standardization allows us to control for market conditions. Trades are defined as the number of orders multiplied their face value. Q_{jik} is the size (face value) of the order which the *jth* dealer receives by *ith* dealer for the *kth* bond.[17] We consider only "informed trade", that is, that part of trade that the dealer engages in after having received an order by a dealer whom he deems to be informed (i.e., γ_{ji} is statistically significant at a 10% confidence level). This allows us to focus only on trades that have a well defined informational content.

I_{ji} represents a measure of the degree of informativeness of the *ith* dealer as perceived by the *jth* dealer. As alternative measures of the degree of informativeness of the dealer, we consider: the value of the coefficient γ_{ji} (as estimated in equation 26), its statistical significance [18] and the product of the two (γ_{ji} times (*1-p value*)). The first measure represents the degree of informativeness of the specific *ith* dealer who is placing the order, as perceived by the *jth* dealer, the second proxies for the degree of accuracy of the signal. The third measures accounts for the parameter uncertainty of the estimate by weighting the value of γ_{ji} by $(1-p_{ji})$, where p_{ji} is the probability value of γ_{ji} as defined in equation (26).

The *p-value* represents the probability that the coefficient's *t-value* is as large as or larger (in absolute value) that the observed *t-statistic,* assuming the null that γ_{ji} is zero. We use it as a proxy for the confidence that the dealer places on the reliability of his estimates (i.e., γ_{ji}). We can think of it as a rough proxy for parameter uncertainty.

σ_k^2 is a proxy of market uncertainty at the time when the dealer receives the incoming order. It is defined as the variance of the *kth* bond in the 10 minutes before the originating transaction, while d_j is a dummy that controls for the dealer's identity. The individual dealer fixed effect (d_j) allows us to control for the dealer's specific characteristics. Sampling is based on transaction time. The observations are defined at the level of individual dealers and then pooled together. All the estimations are carried out using Hansen's Generalized Method of Moments, with correction on the variance-covariance matrix to control for both heteroskedasticity and autocorrelation. In order to deal with the generated regressors in our estimations, we adopt the Pagan (1984) approach based on instrumental

[17] Both trade and orders are expressed in absolute value.
[18] We used (*1-p value*) instead of *p-value* itself.

variable estimation. The estimation is done using a consistent variance-covariance matrix Generalized Method of Moments estimation.[19]

At this stage we are interested only in testing whether there is a correlation between the informational content of the incoming trade and a dealer's decision to engage in trade. That is we expect that $\beta \neq 0$. 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. We report the results for two different proxies for the degree of informativeness: *p-value* of γ_{ji} estimates and the product of γ_{ji} and (*1-p value*)[20].

Panel A reports the estimates for non-auction periods, while Panel B reports the estimates for auction periods. The results reject the null of no correlation between the informational content of incoming orders and the dealer's choice of engaging in trade. In particular, it appears that both overall and for ordinary market makers β is always positive and statistically significant. This holds for all the alternative ways we have defined the degree of informativeness of the incoming trade. It is interesting to note that specialists trade is affected by informativeness of incoming trade only during non-auction periods. This can be due to the fact that specialists, but virtue of the obligation to participate in the auction are much more likely to use the incoming information in their auction order submission strategy.

These results suggest that on average, a greater informational content of the incoming trade will increase dealers' propensity to engage in trade. Assuming the same price impact of the incoming transactions, the share of trade directly originated by the dealer after having received an order 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 dealers (2.5%). This would be consistent with the prevalence of hiding over experimentation. This is indeed the case. As reported in Table 6, the class of dealers who experiment is lower than that of dealers who hide.

[19] Lags of explanatory variables, overnight, one week, one-month, two-month and three month interest rates are used as instruments. We also performed estimates using WLS and OLS. The results agree with the ones reported.

[20] The results for the third proxy -γ_{ji} itself - are similar to the ones reported and are omitted for the sake of brevity.

5.2 H2: Dealers' reaction to information

The next step is to look at the disaggregated level. This requires us to identify how dealers react to the informational content of the incoming trade. We therefore focus here on how the perceived degree of informativeness of the incoming trade affects the way the dealer receiving it chooses his trading counterpart.

5.2.1 Testing the existence of differential behavior

As a preliminary step we test whether there is a pattern in the way dealers 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 dealers whom the "hit" dealer is approaching. We estimate:

$$P_{jk}^{id} = \alpha + \beta I_{ji} + \delta Q_{jik} + \zeta \sigma_k^2 + \theta d_j + \varepsilon_{jik}, \tag{28}$$

where P_{jk}^{id} is the ratio between all the trades originated by the *jth* dealer in the *kth* bond in the 10 minutes following the originating trade that are directed towards "informed dealers" and the total originated/received trade with which the *jth* dealer is involved in the *kth* bond during the period. We define as informed the dealers that the *jth* dealer "is confident" that are informed. We use three levels of confidence, depending on the certainty on the estimates of equation (26): *p-values* below 10%, *p-values* between 10 and 50% and *p-values* greater than 50%.[21] Q_{jik}, I_{ji}, σ_k^2 and d_j are defined as in equation (27).

If dealers consistently react in a different ways to the incoming information, the $\beta's$ for the different groups should be different. That is, we should find a relationship between the degree of informativeness of the dealers placing the originating trade and the degree of informativeness of the dealers who are the final recipients.

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 dealer who receives it to approach either a very informed dealer or a completely uninformed one. Indeed, the

[21] As in equation (27), we consider only the part of trade that the dealer engages in after having received an order by a dealer whom he deems to be informed.

value of β is stronger for the first and third class.

This polarized reaction at the aggregate level suggests the existence of two main types of reactions. Dealers can either hide their information by trading with less informed dealers, or assess the quality of their information by approaching more informed dealers. The former would entail a negative β, the latter a positive one. At the aggregate level this would show up as a bi-modal distribution with the values of $\beta' s$ particularly high for the very informed and very uninformed counterparts. These results also imply that, in aggregate, dealers react systematically to the information contained in the orders they receive by attempting to hide it.

5.2.2 Identification of alternative strategies

However, this specification does not answer the question of whether the same dealer simultaneously plays both strategies, hiding and experimenting. Indeed, only the analysis at the dealer level can address this issue. Unfortunately, risk aversion - that is, what we assume to be the main discriminant of dealers - cannot be directly observed, nor does our dataset provide us with an immediate proxy for it. We therefore proceed in the following way. We first *identify dealers in-sample* by using their reaction to the incoming orders and group them accordingly. This allows us to define groups on the basis of their behavior: dealers who try to hide the informational content contained in the incoming trade (sneakies) and dealers who try to assess its value (skeptics). The former would try to hide, by placing orders with less informed dealers, the latter would try to experiment by placing orders with more informed ones. Therefore, the classification on the basis of risk aversion is "by implication".

Then, *we test out-of-sample* the behavior of these groups. The procedure, reminiscent of the portfolio-formation and testing process usually applied in asset pricing literature, allows us to control for potential endogeneity and sample selection bias (Roll and Ross (1980), Conway and Reinganum (1988)).

In order to identify dealers on the basis of their reaction functions, we use an econometric approach that explicitly models the decision process of an individual facing different choices. The choice space is defined on the basis of the tree of alternatives (Figure 1). The dealer can either operate only by changing the bid and ask quotes and/or withdrawing from the market, or he can directly place orders with other dealers. If the dealer decides to place orders directly with other dealers, he has also to choose which one to approach.

The alternative choices are defined by grouping the dealers in classes according to their degree of informativeness as perceived by the dealer who is placing the order with them. Each class represents a "typology of dealer" with whom the dealer can choose to place orders. We consider five different classes ($c = 1:5$), depending on the value of the γ_{ji} coefficient and its statistical significance.[22] Class I comprises the dealers whom the first dealer is very 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. That is, dealers who have a $\gamma_{ji} > 0$ and p *value* ≤ 0.1 Class II comprises the dealers whom the first dealer is confident (with confidence between 50 and 90%) are able to successfully time the market ($\gamma_{ji} > 0$ and $0.1 <$ p *value* ≤ 0.5). Class III comprises the dealers about whom the first dealer has little knowledge (p *value* > 0.5), Class IV comprises the dealers whom the first dealer is confident (with confidence between 50 and 90%) ($\gamma_{ji} < 0$ and $0.1 <$ p *value* ≤ 0.5) follow contrarian strategies. Finally, Class V comprises the dealers whom the first dealer is very confident (with confidence in excess of 90%) ($\gamma_{ji} < 0$ and p *value* ≤ 0.1) follow contrarian strategies. These dealers 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.[23]

Both classes I and V can be considered as informed dealers who have different information. This implies that the decision of a dealer hit by a dealer belonging to class I (V) to approach a dealer belonging to class V (I) can be interpreted as hiding. The reason being that the hit dealer is approaching a dealer who either has information that is different from

[22] It is worth noting that we separate the dealers into 5 groups on the basis of the p *value* of the coefficient γ_{ji}, while we use the product of $(1-p)$ and γ_{ji} to identify the dealers in terms of degree of informativeness. The reason is that the degree of informativeness is potentially unbounded, while the p *value* is bounded betwen 0 and 1. The degree of informativeness takes into account not only the confidence in the degree of informativeness (p), but also the impact on the market (γ) of such a dealer. Therefore, it is a better measure to describe the choice as it captures the "likely impact" on prices that trading with a particular dealer involves.

[23] 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. Given the oddity of a behavior *consistently money-losing*, a dealer who receives an order from them, even if he is very confident about their behavior, is not as sure how to interpret it. This adds further uncertainty.

that the originating dealer, or plays a different type of strategy. Therefore, he expects the other not to be able to make use of the additional information he is providing with his order.

It is worth remembering that *each individual dealer has a different opinion about all the other dealers in the market and ranks them differently*, depending on the history of the trades he has had with them. Furthermore, the fact that information is in general short-lived, implies that our classification, based on equation (26), is updated every day.

We proceed as follows. At the beginning of the day, for each dealer, we group all the other dealers depending on the priors he has on them (i.e., γs), using the above mentioned criteria. Then, for each dealer we define the orders he places according to the class of dealers with whom he is trading. The placement of an order with a dealer belonging to a particular class represents a choice, and the frequency of the choice is given by the number of transactions during the specified time interval. We build upon the standard discrete choice framework (Anderson, Palma, and Thisse (1994) and Berry (1994)) and represent the choice of the *jth* dealer to place an order with a dealer belonging to the *cth* class as:

$$P_{jk}^{c} = \alpha + \beta I_{jc} + \delta C_{jc} + \zeta \sigma_k^2 + \mu_j + \eta_{jc}, \tag{29}$$

where P_{jk}^{c} is the ratio between all the orders in the *kth* bond that the *jth* dealer places with the dealers belonging to the *cth* class in the 10 minutes following the originating trade and the orders in the same bond that he receives during this period. This standardization helps to control for market conditions. In the Appendix we derive an explicit rationale for this standardization in terms of a discrete choice model.

σ_k^2 is the variance on the *kth* bond in the 10 minutes before the originating transaction, and C_{jc} is a control variables defined as the ratio between the orders in the *kth* bond that the *jth* dealer places with the dealers belonging to the *cth* class in the 10 minutes following the originating order, and the total volume of orders in the *kth* bond that, during the same interval, the *jth* dealer places with all the dealers. In the Appendix we provide a formal description of the choice model that leads to the inclusion of this variable.

The terms μ_j and η_{jc} are noise terms. μ_j proxies for some characteristics observable by the dealer, but not perceived by the econometrician. It controls for the distribution of dealers' preferences and plays the role of "mean of the valuations that each dealer has of the other dealers." This includes things such as "club relationship", preferential treatments, and so on.

I_{jc} represents the *relative* informativeness of the *cth* class of dealers with whom the *jth* dealer chooses to deal. It is constructed as the difference between the informativeness of the dealer placing the originating order and the *average* informativeness of the dealers belonging to class c (and therefore indexed as c) whom the "hit" dealer approaches.[24]

Equation (29) is estimated for each dealer separately on the basis of transaction time. A cross-validation technique is used to identify the classes of dealers, to group them and to test the stability of such a grouping. In particular, we split the sample into odd and even days. Then we estimate equation (29) on the odd days. We use the values of the estimated coefficients β to identify the classes the dealers belong to and then group the dealers according to this classification.

Dealers are classified into three groups based on the nature of their response to informed trade (coefficient β). We will define as sneakies the dealers for whom β is negative and statistically significant and skeptics the dealers for whom β is positive and statistically significant. The rest are dealers for whom β is not statistically significant. Then, we use the sample period based on even days to estimate the value of the aggregated coefficients.[25] We expect that:

$$\beta^{skeptics} > 0 \text{ and } \beta^{sneakies} < 0, \tag{30}$$

that is, skeptics tend to place orders with more informed dealers, while sneakies tend to place orders with less informed ones.

In Table 5, Panels A, B and C we report the results estimated *out-of-sample* and based on grouping the dealers according to the institutional classification as well as to the trading-based classification defined *in sample*. The results support our hypotheses. There are different patterns of behavior among the classes of dealers. In general, *sneakies* try to hide their information. In order to do this, they direct their trade towards dealers less informed than the ones who have hit them. Therefore, if they are hit by class I

[24] In order to account for parameter uncertainty, the proxy for informativeness of dealer i as perceived by dealer j is defined as before by weighting the value of γ_{ji} by $(1 - p_{ji})$, where p_{ji} is the probability value of γ_{ji} .

[25] 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.

dealers, they place order with class II, III, IV and V dealers. Empirically, this corresponds to positive and strongly significant $\beta = 90.10$. Also, if they are hit by class V dealers, they place orders with class II, III and IV dealers (estimate of $\beta = -128.44$ is strongly significant, *t-statistics* is -8.76). That is, they always "go for the centre", towards the less informed.

The *skeptics* behave in the opposite fashion, placing orders with dealers more informed than the ones they receive orders from. That is, if they are hit by class II dealers, they approach class I dealers. Estimates in Table 5, Panel A, show that in the case $\beta = -96.16$ with *t-statistics* -4.62. Alternatively, if skeptics are hit by class IV dealers, they approach class V dealers ($\beta = 87.02$). Unlike the sneakies, they always go for the "wings", toward the extreme classes (I and V).

The rest of the dealers 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 decide not to engage in trade at all when they are hit by contrarians or averages, although they hide when hit by market timers. In the latter case, they tend to approach dealers less informed than those who have hit them. That is, in general they tend to hide. This fits with previous results and confirms the fact that dealers on average tend to hide the information they receive.

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

If we consider the corporate characteristics of the dealers, 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 a larger 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, greater cautiousness.[26]

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

5.3 H3: Dealers' strategies and the cost of experimentation

The next step is to assess how dealers' strategies change as the costs and benefits of experimentation change. The event during which *both* the cost of engaging in trade to experiment as well as the reward it generates in terms of additional information rise is the period before the auction of Treasury bonds. Indeed, the auction provides some dealers with an information advantage, as the dealers who intermediate the biggest share of bonds being auctioned off have additional information about the overall market demand schedule and liquidity shocks. Therefore, experimenting before the auction is costly as it reveals information that could be used profitably *both in the secondary market and at the auction.* At the same time, this feature also increases the value of experimentation.

In particular, we have different testable implications at the aggregated level and at the disaggregated level. At the *aggregated level*, restriction H3 suggests that:

$$\beta_{day\,before\,auction} \neq \beta_{non-auction\,days}. \tag{31}$$

In order to test it, we re-estimate equation (28) for the days before the auction and compare the results for the non-auction days.

The results, reported in Table 4, Panel B, confirm a change in the reaction to informed trade. In particular, while the specialists reduce their information-driven trades, the ordinary dealers seem to increase them. For example, in the case where the coefficient on the informativeness of the incoming dealer is measured by using the *(1-p value)* (I_{p-val}), β increases 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 the propensity to trade after having received an order is channeled through an increase in orders placed with less informed dealers. A

[26] Unfortunately no further investigation in greater detail is allowed by confidentiality requirements.

quick glance at Table 4 shows that the days before the auction the ordinary dealers redirect their trade towards less informed dealers. This indicates that they choose to engage in trade in order to hide and not to experiment. This intuition can be further investigated at the disaggregated level.

At the *disaggregated level*, we re-estimate equation (29) with the use of interactive dummies to control for the days before the auction. In particular, we estimate:

$$P_{jc} = \alpha + \left[\beta^{NA}(1 - D_{BOA}) + \beta^{A} D_{BOA}\right] I_{jc} + \zeta\sigma_k^2 + \delta C_{jc} + \mu_j + \eta_{jc}, \qquad (32)$$

where D_{BOA} is a dummy that is equal to 1 for the transactions in bonds that are auctioned off the next day and zero otherwise[27]. All the other variables are defined as before. We expect that, if the informativeness of the incoming signal is high,

$$|\beta^{A}| > |\beta^{NA}| \text{ for both the skeptics and the sneakies.} \qquad (33)$$

That is, the incremental cost of engaging in trade before the auction should increase the propensity of the skeptics to place orders with more informed dealers and the propensity of the sneakies to place orders with less informed dealers. This means that the increase in the cost of trading makes dealers' reaction function steeper.

The results, reported in Table 5, Panel C, support our working hypothesis. Both β^{A} and β^{NA} are strongly significant and negative for the skeptics and positive for the sneakies. In particular, the values of the coefficients are always greater during auction periods (164.32 and 198.91 versus 78.95 and 61.72, respectively for skeptics and sneakies). Also, we performed a Wald test of the significance of the difference between β^{A} and β^{NA} coefficients. The results show that the difference in the value of the coefficients is statistically significant for both groups.

5.4 H4: Dealers' strategies and market volatility

The next step is to test whether market volatility affects dealers' strategies. As a preliminary evidence, we consider the impact of volatility on informed trading for the different

[27] While estimating eq. (29) we omitted the transactions that involved bonds not auctioned off for the auction days.

classes of dealers. The results, reported in Table 5, Panels A and B, show that volatility always strongly affects dealers' reaction. In particular, volatility increases informed trading for the sneakies and reduces it for the skeptics.

To directly test restriction H4, we estimate equation (29) by separating the sample 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. We expect that:

$$|\beta^{high\ \sigma}| < |\beta^{low\ \sigma}| \text{ for the skeptics and } |\beta^{high\ \sigma}| > |\beta^{low\ \sigma}| \text{ for the sneakies.} \tag{34}$$

The results are reported in Table 5, Panel D where we separate the sample in periods of high and low volatility. They show that in general those conditions are satisfied for relevant classes (I, II, IV and V). That is, an increase in market volatility drastically reduces the reaction to the informational content of trade for the skeptics and increases it for the sneakies. These results also agree with the others (Table 5, panels A and B), suggesting stability of the previous findings.

6 Conclusions

By using a unique dataset that traces dealers' behavior on the Italian Treasury bond market, we have analyzed how dealers learn from past experience of trade with each other and provided evidence of experimentation. We have shown that dealers learn actively from the dealers they trade 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 have shown under which conditions experimentation is the preferred strategy.

These results open up a new and interesting avenue of research. In particular, if market makers react differently to the information they receive, the impact on market prices also differs. From this perspective, it may be possible to use dealers' 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 dealers' strategic interactions.

A Dealer's Learning Problem

Proof of Proposition 1

Dealers 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 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 $\beta \in \mathsf{E}$ is:

$$\pi_\beta(t) = p_\beta(t) + \int_0^t \Re\pi_\beta(u)du + \int_0^t \pi_\beta(u)\frac{A_u(\beta,\xi) - \overline{A}_u(\xi)}{B_u(\xi)}d\overline{W}_u \tag{35}$$

where: $\Re\pi_\beta(u) = \sum_{\gamma\in\mathsf{E}} \vartheta_{\gamma\beta}(u)\pi_\gamma(u)$, $\overline{A}_u(\xi) = \sum_{\gamma\in\mathsf{E}} A_u(\gamma,\xi)\pi_\gamma(u)$ 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 (35), we have:

$$d\pi_{\mu_H} = \mu_{\pi_{\mu_H}} dt + \frac{(1+q_i)}{\sigma^2}\Sigma d\nu, \tag{36}$$

where

$$\mu_{\pi_{\mu_H}} = (1 - 2\pi_{\mu_H})\vartheta, \Sigma = \frac{\pi_{\mu_H}(1-\pi_{\mu_H})(\mu_H - \mu_L)}{\sigma_\xi}$$

and

$$d\nu = \frac{(1+q_i)}{\sigma^2\sigma_\xi}\left(\frac{ds}{s} - \left[\pi_{\mu_H}\mu_H + (1-\pi_{\mu_H})\mu_L\right]dt\right).$$

B The choice model

We build upon the standard discrete choice framework developed by Anderson, De Palma and Thisse, (1994) and Berry (1994). Let' s suppose there are $c = 1, ..., C+1$ choices and define the payoff of the *cth* choice for the *jth* dealer as:

$$u_{jc} = I_c\beta_c + \mu_c + \varepsilon_j \tag{37}$$

Equation (37) implies that the payoff of each individual dealer is a function of the characteristics of the other dealers he deals with (I_c) and some characteristics observable by the dealer, but not perceived by the econometrician (μ). A noise term ε_j is given by the distribution of dealers' preferences (risk aversion, etc.). The *jth* dealer selects the action that guarantees a payoff higher than that of the other alternatives, that is

$$u(I_c, \mu_c, \varepsilon_j, \theta_d) > u(I_{-c}, \mu_{-c}, \varepsilon_j, \theta_d),$$

where θ_d is the set of choices. The probability of choosing the *cth* alternative over the others (-c) alternatives can be represented by:

$$s_j(\xi(I,\mu), I, \theta) = \int_{A_{c(\xi)}} f(\varepsilon, I, \theta_\varepsilon) d\varepsilon \tag{38}$$

where s_c is the probability that the *cth* alternative is chosen and ξ is the mean payoff associated with its choice. It is calculated by integration over the area $A_{c(\xi)}$, that is across all the possible choices.

We assume that the dealer can choose whether to change the bid-ask spread ("*pas*") or to directly engage in trade ("*act*"). We will define the latter case as "active trade". In this case, the dealer also has to choose which other dealer to approach. The set of active choices is $c = 1, ..., C \in act$. The $C + 1^{th}$ choice is the decision to change the bid-ask spread ("*pas*"). We also assume the preferences of the dealer ε_j to be i.i.d. with "extreme value" distribution function, characterized by the parameter δ. We can represent the probability of selecting the *cth* alternative as a function of the average value of its characteristics (ξ), so that:

$$\xi_c = I_c\beta_c + \mu_c. \tag{39}$$

The probability of selecting the *cth* alternative in a one-step decision process becomes:

$$s_c(\xi) = s_{c|act}(\xi, \delta) s_{act}(\xi, \delta), \tag{40}$$

$$\text{where } s_{i|act}(\xi,\delta) = \frac{\exp(\frac{\xi_j}{1-\delta})}{\sum_{c\in act}\exp(\frac{\xi_j}{1-\delta})} \tag{41}$$

represents the probability of choosing the *cth* alternative *once the decision of placing trade directly with other dealers has been taken,* and

$$s_{act}(\xi,\delta) = \frac{(\sum_{c\in act}\exp(\frac{\xi_i}{1-\delta}))^{(1-\delta)}}{(\sum_{c\in act}\exp(\frac{\xi_i}{1-\delta}))^{(1-\delta)} + \exp(\xi_{pas})} \tag{42}$$

represents the probability of directly placing an order with another dealer relative to the overall probability of intermediating a trade (i.e., placing an order with another dealer or receiving an order). "*pas*" represents the "outside" alternative, that is the mere change of the bid-ask spread. The coefficient δ represents the degree of heterogeneity across alternative choices. It ranges from zero to one. When it is equal to zero, the choices are perceived as different from one another. When it is equal to one, 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 38), we can invert this relationship so as to express the probability of choosing an alternative as a function of the mean payoff. By equalizing the probability derived from equation 38 to the actual choices directly observed on the market ($\hat{s}_c$), we can derive the reaction functions of the dealers. In particular, for the *jth* dealer selecting the *cth* alternative:

$$\ln(s_{j,c}) - \ln(s_{j,pas}) = \beta I_{jc} + \delta\ln(s_{j,c|act}) + \mu_j + \eta_{jc} \tag{43}$$

(Berry (1994)). This specification relates the choice of the *jth* dealer to the degree of informativeness of the *cth* class of dealers he chooses to deal with (I_{jc}) and to some characteristics observable by the dealer, but not perceived by the econometrician (μ_j).

The variable $s_{j,c}$, for $c = 1, ..., 5$, is the probability that the *jth* dealer would select the *cth* alternative. It is defined as the ratio between the orders that the *jth* dealer places with the dealers belonging to the *cth* class in the 10 minutes following the originating trade, and the total volume of trade he is involved in (i.e., both the orders he places and the ones that are placed with him) during the same interval.

The variable $s_{j,pas}$ is the probability that the *jth* dealer would receive an order by some other dealer. It is defined as the ratio between the orders that the *jth* dealer receives from other dealers in the 10 minutes following the originating order, and the total volume of trade he is involved in (i.e., both the orders he places and the ones that are placed with him) during the same interval.

Finally, $C_{jc} = \ln(s_{j,c} / \sum_{c=1}^{5} s_{j,c})$ is the probability that the *jth* dealer would select the *cth* alternative, *conditional* on having decided to place orders with other dealers. That is, it is the ratio between the orders the *jth* dealer places with other dealers belonging to the *cth* choice group in the 10 minutes following the originating order, and the total volume of orders that, during the same interval, the *jth* dealer places with all the other dealers.

The coefficient δ represents the degree of heterogeneity across alternative choices. 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 δ 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. In the specification based on the institutional classification, the ordinary dealers always have a degree of heterogeneity lower than that of the specialists. This is intuitive, as the ordinary dealers, being less informed, are more likely to resort to experimentation. Therefore, they consider the dealers they are approaching as different in terms of their informational content. The specification we estimate is:

$$P_{jc} = \alpha + \beta I_{jc} + \delta C_{jc} + \zeta \sigma_k^2 + \mu_j + \eta_{jc}, \tag{44}$$

where $P_{jc} = \ln(s_{j,c}) - \ln(s_{j,pas})$, $C_{jc} = \ln(s_{j,c|act})$ and a control variable to account for volatility (σ_k^2) has been added.

C Robustness Checks

This section of the 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 dealers, we also consider an alternative criterion based on the separation of dealers according to their volume of trading in the secondary market. For each month, we calculate the trading volume of each single dealer in the market and then we group the dealers into quartiles on the basis of their total volume.[28] The specialists always coincide with the biggest dealers, falling into the first quartile, while the ordinary dealers fall mostly into the second, and partly into the third quartile. Ordinary dealers belong partly to the third and mostly to the fourth quartile.

We also experiment with extending the reaction period to 30 minutes. That is, we consider all the trades intermediated by the dealer 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 dealers' induced trade, as well as to dealers' inability to move the bid-ask spread in time to avoid being "picked off" by other informed agents when there is an information arrival (as in Foucault, Roell, and Sandas (1999).) Extending the window, we are better able to control for the possibility that the dealer is systematically being picked off by successive dealers placing orders before he has had time to adjust his bid-ask spread.

In the case where the dealer 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 "pick-off" does not affect our story. 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 dealer to change his bid and ask.

C.2 H2: Preliminary testing of informativeness of trades

C.2.1 Controlling for different definitions of variables

We experiment with different "learning and reaction windows". In particular, we extend

[28] Alternatively, we also group dealers 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.

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 dealers behave differently, we expect learning not to be the same in the two regimes and the prior on the degree of informativeness of specific dealers to diverge. The results agree with those based on a single learning matrix for the whole period.

C.2.2 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 dealer. We therefore estimate the following specification:

$$\Delta P_k = \gamma_{ji} T_{jik} + \delta \Delta P_{k,-5} + \varepsilon_{jik} \tag{45}$$

where $\Delta P_{k,-5}$ represents the change of prices in the past 5 minutes of the *kth* bond.[29] The results of the estimate seem to indicate that the trade of ordinary dealers is somewhat driven by momentum considerations, but in all the other aspects, the results agree with the ones reported in the text.

C.2.3 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 dealers orthogonal to total trades (ε_{jik}), and then we see how much of it is explained by our measure of informed trade. In particular, we estimate:

$$q^l_{jik} = a + bQ_{jik} + \varepsilon_{jik}$$

[29] We thank Y. Amihud for bringing this point to our attention.

where Q_{jik} is the incoming trade (signed), q^l_{jik} is outgoing trade (signed) originated by the dealer j ($l = outgoing$) and intermediated by him ($l = incoming$), and the variable ε_{jik} is orthogonal to total trades. This is then regressed on informational trade according to:

$$\varepsilon_{jik} = \alpha + \beta \times \gamma Q_{jik} + \eta_{jik} \tag{46}$$

It is worth noting that the additional explanatory power of T^{Inf}_{jik} is due to the learning coefficient γ that multiplies the part of total trades (Q_{jik}) that are identified as "informed".[30] A second specification directly separates the informational effect from the pure inventory one:

$$q^l_{jik} = a + bQ_{jik} + \delta Inv_{jik} + \varepsilon_{jik}, \tag{47}$$

where Inv_{jik} is the *ith* dealer's inventory position on the kth bond. In particular, for each dealer, we construct inventory (Inv_{jik}) as a time series based on dealers' purchases and sales over time. We use the definition of inventory of Hansch, Naik, and Viswanathan (1998), calculating the standardized inventory:

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

where for each bond *k*, $E_{Inv_{jik}}$ and $\sigma_{Inv_{jik}}$are, respectively, the mean and the standard deviation of inventory over the sample. If dealers 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 dealers' trading reactions. A positive sign of β implies that dealers react to informed trade, while a positive δ is a sign of inventory-driven behavior.

The results for the first specifications shows that the trade originated by the dealer is indeed associated with "informed" trade ($b's$ are strongly statistically significant), whereas $b's$ for intermediated trade are not significant. Estimation of the second specification shows that $\delta's$ are not significant. Those results holds for both institutional and trade-based specifications of dealers. Thus, it seems that the inventory-based explanation for our results can indeed be ruled out.

[30] 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.

C.2.4 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:

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

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: dealers' 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 the dealer receives orders by other dealers in the 10 minutes after the originating trade and where the dealer 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 dealer-originated transaction in the 10 minutes following the originating trade.[31] In the second specification, we consider all the cases, assigning a weight of 100% to the choice of the outside alternative (s_0) 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 dealer 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

[31] 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.

from the market. In this case we use clock time. The results agree with the ones reported in the text.

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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 dealers and volume broken down on the basis of both intermediating dealer 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 dealer	Total	Specialists	Ord. Mkt Makers	Ord. Dealer
Specialists	727,747	262,684	292,498	172,565
Ord. Mkt 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 dealer				
Specialists		658.85	384.46	4175
Ord. Market Makers		283.57	258.50	2550
Intermediating dealer	**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 (26)

$$\Delta P_k = \gamma_{ji} Q_{jik} + \varepsilon_{jik}.$$

For each trading day we consider the pairwise relation of each dealer j versus all the other i dealers in previous ten trading days. ΔP_k is the change in price of the *kth* bond in the 5 minutes following the originating transaction while γ_{ji} represents the degree of informativeness of the specific dealer. Q_{jik} is the signed volume received by the *jth* dealer from the *ith* dealer for the *kth* bond. We report the results of *t-test* for the mean of γ_{ji}. We report statistics for γ_{ji} averaged over all dealers separated over both intermediating dealer and type of dealer originating the trade. Dealers are grouped according to the institutional classification (Panels A and B) and to the trading-based classification (Panels C and D). Panels A and C contain the statistics for all γ_{ji} and Panels B and D only for the statistically significant ones (at 10% level). The values of 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		486,002	0.39	1.54	-23.47	21.42	177.5
Intermediating dealer	**Originating dealer**						
Specialist	Specialist	63,154	0.43	1.03	-8.76	8.91	105.24
Specialist	Market Maker	115,182	0.36	1.39	-13.82	12.22	87.19
Specialist	Ord. Dealer	35,867	0.14	1.92	-19.90	18.65	13.57
Market Maker	Specialist	104,432	0.50	1.43	-12.53	20.18	113.73
Market Maker	Market Maker	131,172	0.44	1.63	-16.88	16.97	98.15
Market Maker	Ord. Dealer	36,195	0.18	2.12	-23.47	21.42	16.33

Panel B: Learning coefficient γ_{ji}, Institutional Classification of Dealers, statistically significant γ_{ji} only

		N	Mean	Std.Dev.	Min.	Max	t-statistics
Overall		57,634	1.30	2.52	-23.47	21.42	123.6
Intermediating dealer	**Originating dealer**						
Specialist	Specialist	9,611	1.31	1.37	-8.76	8.91	94.1
Specialist	Market Maker	12,661	1.27	2.29	-12.82	12.22	62.3
Specialist	Ord. Dealer	4,027	0.47	3.66	-19.90	18.65	8.12
Market Maker	Specialist	13,062	1.57	2.15	-10.73	13.55	83.3
Market Maker	Market Maker	14,091	1.51	2.66	-15.65	12.27	67.5
Market Maker	Ord. Dealer	4,182	0.62	3.87	-23.47	21.42	10.3

Table 2, continued.

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

Intermediating dealer	**Originating dealer**	N	Mean	Std.Dev.	Min.	Max.	t-statistics
Skeptic	Skeptic	1,912	0.23	1.68	-10.88	9.81	6.08
Skeptic	The rest	29,884	0.54	1.57	-12.43	21.13	59.01
Skeptic	Sneaky	6,857	0.72	1.23	-5.96	8.17	48.76
The rest	Skeptic	22,891	0.15	1.47	-8.54	20.18	15.41
The rest	The rest	268,590	0.39	1.59	-23.47	21.42	127.07
The rest	Sneaky	63,465	0.58	1.38	-15.65	16.85	106.55
Sneaky	Skeptic	6,053	0.02	1.47	-11.16	10.11	1.05
Sneaky	The rest	72,181	0.24	1.55	-14.40	12.66	42.19
Sneaky	Sneaky	14,169	0.48	1.34	-7.29	11.00	42.41

Panel D: Learning coefficient γ_{ji}, Trading-based Classification of Dealers statistically significant γ_{ji} only

Intermediating dealer	**Originating dealer**	N	Mean	Std.Dev.	Min.	Max.	t-statistics
Skeptic	Skeptic	187	1.37	3.18	-10.88	9.82	5.92
Skeptic	The rest	3,858	1.61	2.38	-11.86	18.65	41.95
Skeptic	Sneaky	1,156	1.82	1.33	-5.00	8.17	46.82
The rest	Skeptic	1,862	0.55	2.80	-8.54	11.80	8.53
The rest	The rest	29,134	1.28	2.65	-23.47	21.42	82.72
The rest	Sneaky	9,530	1.69	1.91	-15.65	12.23	86.64
Sneaky	Skeptic	678	0.24	2.85	-2.85	10.11	2.16
Sneaky	The rest	9,006	0.93	2.75	-12.45	12.42	31,87
Sneaky	Sneaky	2,223	1.47	1.99	-7.29	11.00	34.89

Table 3. A first test of strategic behavior

We report the results of the estimation of the model:

$$P_{jk} = \alpha + \beta I_{ji} + \delta Q_{jik} + \zeta\sigma_k^2 + \theta d_j + \varepsilon_{jik},$$

where P_{jk} is the ratio between the all the trades the jth dealer places in the kth bond in the 10 minutes following the originating trade and the total trade he executes in the kth bond during the same time period (i.e., the orders he places directly with other dealers as well as the orders he receives).Trades are defined as the number of orders multiplied their face value. Q_{jik} is the size (face value) of the order which the jth dealer receives by ith dealer for the kth bond. We focus only on "informed trade", that is, that part of trade that the dealer engages in after having received an order by a dealer whom he deems to be informed (i.e., γ_{ji} is statistically significant at a 10% confidence level). I_{ji} represents a measure of the degree of informativeness of the ith dealer as perceived by the jth dealer. As alternative measures of the degree of informativeness of the dealer, we report: the value of the coefficient γ_{ji} (I) and the product of γ_{ji} and *(1-p value)* (I_{Pval}). σ_k^2 is a proxy of market uncertainty at the time when the dealer receives the incoming order. It is defined as the variance on the kth bond in the 10 minutes before the originating transaction, while d_j is a dummy that controls for the dealer's identity. The individual fixed effect (d_j) allows us to control for the dealer's specific characteristics. Sampling is based on transaction time. The observations are defined at the level of individual dealers and then pooled together. The estimation is done using a consistent variance-covariance matrix Generalized Method of Moments estimation. Lags of explanatory variables, overnight, one week, one-month, two-month and three month interest rates are 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 Dealer	N	Constant	I	I_{Pval}	σ_k^2	Q_{jik}	p_H
Overall	24,478	0.54	12.08	-	-3.41	-.001	0.33
		(71.70)	(2.82)	-	(-2.79)	(-2.29)	
		-2.38	-	2.99	-2.76	-.006	0.33
		(-3.92)	-	(4.84)	(-2.95)	(-3.19)	
Specialist	16,378	0.53	9.96	-	-2.79	-.0006	0.26
		(56.31)	(2.01)	-	(-2.18)	(-0.96)	
		-2.73	-	3.34	-2.58	-.0009	0.75
		(-3.95)	-	(4.75)	(-2.39)	(-1.52)	
Ordinary Market Maker	8,100	0.54	19.49	-	-4.80	-.002	0.30
		(46.39)	(3.21)	-	(-2.55)	(-3.47)	
		-1.89	-	2.52	-2.71	-.003	0.93
		(-1.79)	-	(2.33)	-1.59	(-4.31)	

Panel B: Auction periods

Intermediating Dealer	N	Constant	I	I_{Pval}	σ_k^2	Q_{jik}	p_H
Overall	3,709	0.55	7.59	-	-8.23	-.003	0.22
		(30.40)	(0.72)	-	(-1.75)	(-2.44)	
		-2.13	-	2.54	-7.40	-.004	0.98
		(-1.93)	-	(2.45)	(-1.73)	(-2.92)	
Specialist	1,200	0.56	-0.51	-	-11.59	-.005	0.63
		(20.79)	(-0.03)	-	(-1.69)	(-2.55)	
		1.75	-	-1.21	-11.72	-0.005	0.99
		(1.02)	-	(-0.69)	(-1.86)	(-2.47)	
Ordinary Market Maker	2,509	0.52	27.84	-	-8.59	-.001	0.17
		(21.20)	(2.02)	-	(-1.63)	(-0.75)	
		-4.11	-	4.75	-5.76	-.003	0.99
		(-3.06)	-	(3.48)	(-1.17)	(-1.62)	

Table 4. Testing the existence of differential behavior

We reports the results of the estimation of the equation:

$$P_{jk}^{id} = \alpha + \beta I_{ji} + \delta Q_{jik} + \zeta\sigma_k^2 + \theta d_j + \varepsilon_{jik},$$

where P_{jk}^{id} is the ratio between all the trades originated by the jth dealer in the kth bond in the 10 minutes following the originating trade that are directed towards "informed dealers" and the total originated/received trade with which the jth dealer is involved in the kth bond during the period. We define as "informed" the dealers that the *jth* dealer "is confident" that are informed. We use three "levels of confidence", depending on the certainty on the estimates of equation (26): p-values below 10%, *p-values* between 10 and 50% and *p-values* greater than 50% (*High* Informativeness or *p-value* of γ_{ji} below 10%), average beliefs (*Medium* Informativeness or p value of γ_{ji} between 10 and 50%) and weak beliefs (*Low* Informativeness or p value of γ_{ji} above 50%). Q_{jik}, I_{ji}, σ_k^2 and d_j are defined as in Table 3. The estimation is done using a consistent variance-covariance matrix Generalized Method of Moments estimation. Lags of explanatory variables, overnight, one week, one-month, two-month and three month interest rates are used as instruments. The *t-statistics* of estimates are reported in brackets. p_H is the p *value* of Hansen's overidentification criterion. We test the specification for the days before the auction ("Auction periods") and compare the results for the non-auction days ("Non-Auction periods").

Table 4, continued.

Panel A: Non-auction periods

Intermediating Dealer	**Informativeness of Final Recepient**	**Variable**					
		Constant	I	I_{Pval}	σ_k^2	Q_{jik}	p_H
Overall	High	0.60	72.24	-	-10.5	-.002	0.99
(N=24,478)		(42.26)	(8.21)	-	(-3.69)	(-3.69)	
	Medium	0.33	-12.96	-	9.42	-.0001	0.23
		(28.29)	(-1.99)	-	(4.60)	(-0.25)	
	Low	0.51	56.3	-	-3.89	-.003	0.12
		(29.97)	(5.73)	-	(-1.58)	(-3.43)	
	High	-5.64	-	6.47	0.07	-.004	0.42
		(-5.29)	-	(5.96)	(0.03)	(-5.07)	
	Medium	5.30	-	-5.09	8.73	.0002	0.99
		(5.99)	-	(-5.65)	(5.32)	(0.31)	
	Low	-10.66	-	11.47	0.96	-.0041	0.10
		(-6.34)	-	(6.70)	0.40	-3.63	
Specialists	High	0.63	61.95	-	-12.63	-.003	0.19
(N=16,378)		(35.26)	(5.50)	-	(-4.24)	(-3.39)	
	Medium	0.32	-8.44	-	9.01	-.0002	0.27
		(22.99)	(-0.99)	-	(3.68)	(-0.26)	
	Low	0.54	25.6	-	-6.15	-.0031	0.81
		(25.5)	(2.04)	-	(-1.63)	(-3.14)	
	High	-5.11	-	5.92	-3.21	-.0041	0.71
		(-4.19)	-	(4.78)	(-1.28)	(-4.09)	
	Medium	1.50	-	-1.22	8.99	.0006	0.27
		(1.50)	-	(-1.19)	(4.30)	(0.09)	
	Low	-3.83	-	4.48	-3.76	-.0037	0.40
		(-2.17)	-	(2.51)	(-1.09)	(-3.21)	
Market Maker	High	0.60	62.5	-	-2.51	-.003	0.99
N=8,100		(25.28)	(4.91)	-	(-0.58)	(-2.13)	
	Medium	0.34	-41.23	-	12.06	-.0004	0.37
		(19.48)	(-4.58)	-	(3.72)	(-0.37)	
	Low	0.529	70.04	-	0.787	-.003	0.22
		(20.81)	(5.48)	-	(0.21)	(-2.11)	
	High	-6.32	-	7.17	6.22	-.004	0.97
		(-3.27)	-	(3.63)	(1.80)	(-3.57)	
	Medium	7.19	-	-7.05	6.73	.0007	0.88
		(4.81)	-	(-4.63)	(2.40)	(0.61)	
	Low	-15.87	-	16.85	7.24	-.005	0.61
		(-5.07)	-	(5.27)	(1.71)	(-2.11)	

Table 4, continued.

Panel B: Auction periods

Intermediating Dealer	**Informativeness of Final Recepient**	**Variable**					
		Constant	I	I_{Pval}	σ_k^2	Q_{jk}	p_H
Overall	High	0.67	59.53	-	-5.11	-.009	0.42
(N=3,709)		(20.34)	(2.93)	-	(-0.64)	(-3.74)	
	Medium	0.28	1.58	-	7.68	.001	0.31
		(10.01)	(0.10)	-	(1.34)	(0.56)	
	Low	0.52	86.8	-	-1.71	-.006	0.32
		(13.38)	3.10	-	(-0.22)	(-2.31)	
	High	-5.77	-	6.63	1.98	-.012	0.44
		(-2.97)	-	(3.36)	(0.29)	(-4.61)	
	Medium	7.08	-	-6.91	10.77	.001	0.18
		(3.86)	-	(-3.71)	(2.02)	(0.60)	
	Low	-12.59	-	13.46	-0.22	-.010	0.14
		(-3.16)	-	(3.31)	(-0.03)	(-3.40)	
Specialists	High	0.68	44.81	-	1.63	-.0030	0.81
(N=1,200)		(17.01)	(1.93)	-	(0.19)	(-3.14)	
	Medium	0.32	-11.37	-	8.95	-.0007	0.48
		(9.41)	(-0.57)	-	(1.33)	(-0.33)	
	Low	0.52	70.82	-	1.63	-.007	0.24
		(9.55)	(2.05)	-	(0.19)	(-2.31)	
	High	-4.67	-	5.02	-1.01	-.011	0.23
		(-2.10)	-	(2.45)	(-0.13)	(-3.41)	
	Medium	5.46	-	-5.24	8.34	-.0003	0.31
		(2.83)	-	(-2.67)	(1.31)	(-0.12)	
	Low	-2.49	-	3.17	8.40	-.011	0.20
		(-0.65)	-	(2.01)	(1.14)	(-3.60)	
Market Maker	High	0.71	18.13	-	8.04	-.012	0.17
N=2,509		(6.06)	(0.72)	-	(0.52)	(-3.36)	
	Medium	0.28	-32.13	-	13.35	.002	0.15
		(6.18)	(-1.24)	-	(1.32)	(0.86)	
	Low	0.41	129.81	-	-26.10	-.001	0.59
		(7.17)	(4.66)	-	(-1.67)	(-0.36)	
	High	-5.88	-	6.74	6.52	-.011	0.64
		(-1.69)	-	(1.91)	(0.45)	(-3.02)	
	Medium	4.40	-	-4.25	9.24	.003	0.46
		(1.30)	-	(-1.23)	(1.11)	(1.18)	
	Low	-14.83	-	15.76	-12.9	-.008	0.32
		(-2.37)	-	(2.47)	(-0.50)	(-1.51)	

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

We estimate:

$$P_{jk}^{c}= \alpha + \beta I_{jc}+\delta C_{jc} + \zeta\sigma_{k}^{2}+\mu_{j}+\eta_{jc},$$

where P_{jk}^{c} is the ratio between all the orders in the kth bond that the jth dealer places with the dealers belonging to the cth class in the 10 minutes following the originating trade and the orders in the same bond that he receives during this period. σ_{k}^{2} is the variance on the kth bond in the 10 minutes before the originating transaction, and C_{jc} is a control variables defined as the ratio between the orders in the kth bond that the jth dealer places with the dealers belonging to the cth class in the 10 minutes following the originating order, and the total volume of orders in the kth bond that, during the same interval, the jth dealer places with all the dealers. The terms μ_j and η_{jc} are noise terms. μ_j proxies for some characteristics observable by the dealer, but not perceived by the econometrician. I_{jc} represents the relative informativeness of the cth class with whom the jth chooses to deal. It is constructed as the difference between the informativeness of the dealer placing the originating order and the average informativeness of the dealers belonging to class c (and therefore indexed as c) whom the "hit" dealer approaches. The alternative choices are defined by grouping the dealers in classes according to their degree of informativeness as perceived by the dealer who is placing the order with them. Each class represents a "typology of dealer" with whom the dealer can choose to place orders. We consider five different classes ($c = 1 : 5$), depending on the value of the γ_{ji} coefficient and its statistical significance. Class I comprises the dealers whom the first dealer is very 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. That is, dealers who have a $\gamma_{ji} > 0$ and p value ≤ 0.1 Class II comprises the dealers whom the first dealer is confident (with confidence between 50 and 90%) are able to successfully time the market ($\gamma_{ji} > 0$ and $0.1 <$p value ≤ 0.5). Class III comprises the dealers about whom the first dealer has little knowledge (p value> 0.5), Class IV comprises the dealers whom the first dealer is confident (with confidence between 50 and 90%) ($\gamma_{ji} < 0$ and $0.1 <$p value ≤ 0.5) follow contrarian strategies. Finally, Class V comprises the dealers whom the first dealer is very confident (with confidence in excess of 90%) ($\gamma_{ji} < 0$ and p value ≤ 0.1) follow contrarian strategies. The 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. The equation is estimated for each dealer separately on the basis of transaction time. A cross-validation technique is used to identify the classes of dealers, to group them and to test the stability of such a grouping. We split the sample into odd and even days. Then we estimate equation (29) on the odd days. We use the values of the estimated coefficients β to identify the classes the dealers belong to and then group the dealers according to this classification.

Panels A, B and C reports the results of estimation disaggregated over the precision of incoming signal. In Panel C the specification does not contain σ_{P}^{2}, but the estimations are performed separately for periods of "high" and "low" volatility σ_{P}^{2}. "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. Panel D reports the results of the estimate of:

$$P_{jc}= \alpha+ \left[\beta^{NA}(1 - D_{BOA}) + \beta^{A} D_{BOA}\right] I_{jc}+\delta C_{jc}+\zeta\sigma_{k}^{2}+\mu_{j}+\eta_{jc},$$

where D_{BOA} is the dummy that is equal to 1 for the days before the auctions and transactions involved auctioned bonds and is 0 for non-auction days. In this estimation D_{BOA} was use as an additional instrumental variable. We also report the *p-value* of the Wald test of the hypothesis of $\beta^{NA} = \beta^{A}$. *t-statistics* of the estimates are reported in brackets. The *p value* of Hansen's overidentification criterion (p_H) is reported for each regression.

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

	I		II		III		IV		V	
Skeptic										
α	-0.41	(-19.56)	-0.37	(-24.28)	-0.41	(-19.40)	-0.31	(-8.95)	-0.32	(-4.75)
β	-84.44	(-5.36)	-96.16	(-4.62)	54.28	(1.61)	87.02	(4.15)	36.34	(1.81)
ζ	-32.03	(-1.97)	-97.10	(-8.95)	-36.50	(-2.66)	-4.37	(-0.96)	-103.66	(-3.45)
δ	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		0.11	
N	9,721		12,132		19,411		3,316		755	
The rest										
α	-0.28	(-34.97)	-0.27	(-44.24)	-0.24	(-39.34)	-0.29	(-24.1)	-0.31	(-13.49)
β	33.17	(5.89)	31.73	(4.41)	14.73	(1.06)	-13.79	(-1.66)	-10.53	(-1.18)
ζ	-17.97	(-4.46)	-10.33	(-2.03)	-12.06	(-3.38)	-11.99	(-2.46)	-12.62	(-1.33)
δ	0.47	(60.64)	0.46	(67.91)	0.41	(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										
α	-0.37	(-24.68)	-0.36	(-31.98)	-0.31	(-33.91)	-0.49	(-25.12)	-0.56	(-17.75)
β	66.11	(7.00)	90.10	(6.95)	-19.15	(-0.87)	-128.44	(-8.76)	-99.49	(-8.27)
ζ	24.25	(4.29)	14.48	(2.56)	10.26	(2.21)	32.63	(3.64)	5.51	(0.49)
δ	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		0.11		0.59		0.27	
N	21,728		38,782		86,563		19,919		6,134	

Panel B: Institutional Classification of Dealers, Separation Over Precision of Signal

	I		II		III		IV		V	
Specialist										
α	-0.34	(-40.44)	-0.34	(-50.40)	-0.32	(-43.15)	-0.42	(-30.13)	-0.51	(-20.00)
β	24.70	(3.74)	44.79	(4.85)	11.94	(0.65)	-74.36	(-7.32)	-81.25	(-8.02)
ζ	-11.22	(-2.51)	-8.98	(-2.46)	0.29	(0.12)	4.29	(1.51)	16.22	(1.56)
δ	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										
α	-0.26	(-22.60)	-0.26	(-30.37)	-0.22	(-32.98)	-0.28	(-19.12)	-0.28	(-10.01)
β	29.41	(4.34)	25.69	(3.13)	13.24	(0.97)	-18.99	(-1.95)	-2.11	(-0.20)
ζ	-25.98	(-4.93)	-13.92	(-1.71)	-13.93	(-3.44)	-12.15	(-2.12)	-29.50	(-2.14)
δ	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, Auction vs. Non-Auction Periods, High Precision of Incoming Signal

	Skeptic		The rest		Sneaky	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
α	-0.54	(-24.73)	-0.40	(-44.76)	-0.63	(-26.68)
β^{A}	-164.32	(-3.91)	12.39	(0.56)	198.91	(4.06)
β^{NA}	-78.95	(-5.61)	27.38	(4.35)	61.72	(4.74)
δ	-21.03	(-1.87)	-10.83	(-2.66)	32.28	(4.62)
ζ	0.30	(14.10)	0.47	(57.86)	0.46	(23.81)
N	7,535		44,770		13,177	
p_H	0.15		0.07		0.52	
p value of the test that $\beta^A = \beta^{NA}$	0.063		0.521		0.005	

Panel D: Trading-based Classification of Dealers, 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										
α	-0.43	-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	-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)
δ	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
The rest										
α	-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	25.62	19.56	9.52	3.42	0.754	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)
δ	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										
α	-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	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)
δ	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, The rest 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 dealers intermediate, while the second is based only on the volume they generate (active trade).

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