Reputation and interdealer trading. A microstructure analysis of the Treasury Bond market.*

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Abstract

Trading generates not only information about the payoff of the assets traded, but also information about the traders themselves. Over time this information creates rep utation. By using a unique dataset on the Treasury bond market we derive a measure of reputation. This is then used to group dealers on the basis of their reputation and to analyze how they react to the reputation of other dealers. We show that the same type of trade, on the same asset, in the same market can generate different volume and volatility patterns depending on the type of dealers originating it. We also identify the "marginal traders". These treaders, even if they do not originate the biggest volume of trade, have the highest impact on the market. These results have strong implications in terms of forecastability of future returns, volatility and overall trading volume because they show that most of the explanatory power of trades is due to marginal traders.

1. Introduction

Trading generates information. Traders learn about future asset payoffs and demand shocks, but also about each other. A dealer receiving an order not only acquires information about the traded asset, but also updates his beliefs about his counterpart. Over time this process generates reputation and reputation affects trading behavior. Therefore, traders' reputation may help to explain volume and volatility in terms of market impact of trades originated by otherwise identical traders. In the present paper we empirically address this issue by directly inspecting the role played by dealers' reputation on the mechanism of price formation in a dealership market.

French and Roll (1986) argue that "the process of trading may induce volatility." Since that paper dealers' behavior and the interaction with market trading rules have been widely analyzed. However, the lack of data at a disaggregated level has made it difficult to properly test the role played by the existence of different types of dealers. For example, it is well known that large price movements in the Treasury Bond and FX markets are strongly affected by a release of public information (Andersen and Bollerslev (1998) and Fleming and Remolona (1999)), however it remains unclear how dealers' interaction affects the dynamics of these adjustments. Madhavan, Richardson, and Roomans (1997) recognize that the pricing specification, and therefore volatility and volume, should contain a component that accounts for the way the trade has been intermediated. But they then generically attribute it to imperfections and market frictions without investigating it further[1].

Bessembinder and Seguin (1993) suggested for the first time a connection between the volatility-volume relationship and the type of trader. More recently, Daigler and Wiley (1999), by observing the futures markets, identify two types of traders: the "in-

[1] "The process of trading itself may generate price movements because of various market imperfections and frictions" (Madhavan, Richardson, and Roomans (1997)).

pit" and "out-of-pit" traders. The former are the floor traders and clearing members who have an informational advantage due to the observation of the order flow. The latter are generically defined as "general public". Trading by the informed dealers results in lower volatility, whereas trading by the general public results in increased volatility. In the FX market, Evans and Lyons (1999), Lyons (1995) and Lyons (1997) identify a set of "microstructure-based" variables that help explain the exchange rate dynamics much better than the standard macroeconomic ones.

In all these cases the classification of dealers is based on institutional characteristics (floor traders, clearing members and so on). The goal is limited to incorporating the *institutional* details of the market microstructure into the asset pricing literature, as opposed to directly classifying dealers in terms of their reputation or reaction to other dealers' reputation. Indeed, while reputation has been studied from a theoretical perspective by Sobel (1985) and Benabou and Laroque (1992), no direct empirical investigation of it or estimation of its impact on the market has been carried out. Benveniste, Marcus, and Wilhelm (1992) argue that the information generated by the process of trading, by endowing dealers with private information about the other market participants, implicitly establishes reputation for the dealers. Madhavan and Cheng (1997), analyzing reputation in block trading, show how reputation affects the process of price formation. More recently, Battalio, Jennings, and Selway (2001) argues that the profitability of the order flow depends on the identity of the broker who initiate the trade [2].

The empirical literature which is closer to our analysis in terms of the focus of the analysis and of the usage of data broken down at individual dealer level is the literature on interdealer trading (Gould and Kleidon (1994), Reiss and Werner (1995), Lyons (1995), Hansch, Naik, and Viswanathan (1998) and Reiss and Werner (1998)). In par-

[2] However Battalio, Jennings, and Selway (2001) do not link the profitability with informational advantage.

ticular, both Hansch, Naik, and Viswanathan (1998) and Reiss and Werner (1998) use disaggregated data on dealers' behavior in the London Stock Exchange to test dealers' behavior. They mostly focus on testing the implications of the standard inventory model (Ho and Stoll (1983)) and analyzing dealers' inventory management policies. We complement this literature by focusing on the informational dimension. We consider how 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. Repeated inter-dealer interaction generates information and creates reputation. We want to see whether reputation may affect the mechanism of price formation and, by itself, provide an alternative way of classifying the dealers.

In order to investigate this issue, we focus on interdealer trading and use a unique dataset on the Italian Treasury Bond market that contains the individual transactions of all the dealers active on the market, *disaggregated by dealer and type of bond*. Unlike the US market, where the transactions are mostly over-the-counter, and therefore any analysis would have to be limited to a subsection of the market, the Italian market is a centralized and regulated one where all the transactions are concentrated. This allows us to observe the behavior of the market as a whole.

In particular, we have available for each dealer in the market the complete set of his individual transactions in the secondary market, reported tick-by-tick and detailed by type of bond traded. Moreover, we have also information on the *side that is originating the trade*. This allows us to identify the informed dealers and to test the behavior of this selected small group of agents versus that of the other dealer. We are therefore able not only to endogenously define dealers' reputation, but also to explicitly analyze the type of strategic interaction among them and to quantify the way it affects bond volatility and trading volume.

We consider two dimensions of the impact of reputation on dealers' behavior. First we focus on adverse selection and classify dealers in terms of their perception of the ability of the other dealers surrounding them ("confident" and "scared"). Alternatively, we group them in terms of the perception that the overall market has about their ability ("smart" and "dumb").

Then, we focus on how the reputation of the dealer placing an order affects the way the dealer who receives it assesses its informational content and strategically reacts to it. We therefore group dealers according to whether they try to hide the information they receive by placing orders with dealers less informed than those who have placed orders with them ("sneakies") or they try to assess the quality of their information by placing orders with dealers more informed than those who have placed orders with them ("skeptics").

Among these classes, we identify the "salient" ones (i.e., scared, smart and skeptics), that is the dealers whose trades have the strongest market impact (in the Kyle definition). We show that in the very short run, the market is less deep when the trade has been originated by an salient dealer.

We then analyze the cross-sectional and time-series differences in the impact of the trades originated by different types of dealers on overall trading volume and volatility in the periods following the transactions. We show that trade originated by salient dealers has a stronger impact over time. In particular, a smart dealer impacts on volume and volatility more than a dumb one. A scared dealer impacts on volume and volatility more than a confident dealer and a skeptic has a stronger impact than a sneaky one.

Moreover, we show that the differential impact is still statistically significant at the end of the day and that the daily trade of the salient dealers impacts the market more than the one originated by the other classes of traders. While scared, smart and sneaky dealers tend to increase volatility, confident, dumb and skeptic dealers tend to reduce it. We show that at the daily level, the process of experimentation, by disseminating information earlier, reduces volatility. On the contrary, adverse selection (i.e. trading by scared and smart investors) drives volatility up.

We argue that the fact that salient dealers (scared, smart and sneaky dealers) consistently have a stronger impact both in the short term and in the long term makes their trade an ideal leading indicator of future market conditions. We show that their trades have a higher out-of-sample power to forecast future returns, volume and volatility than the trade of the other classes of dealer as well as the overall aggregated trade, at every time horizon.

Finally, we examine whether differences in impact correspond to differences in profitability. We show that dealers belonging to different classes display statistically different profits for all the trade-based classifications. In particular, we show that experimentation is costly as the skeptics display lower profits than the sneakies who immediately reap the benefit of their informational advantage. Adverse selection induces the scared dealers to enact trades which provide them with consistently lower profits than the ones of the confident investors. The smart investors make more profits.

The paper is structured in the following way. In the next section we present our approach and define the role played by traders' beliefs and reputation. In Section 3 we describe the market. In Section 4 we define and estimate information and reputation and classify traders on the basis of it. In Section 5 we formally lay out the econometric restrictions and report the results of the estimations. In Section 6 we calculate the profits of the different trading strategies. A brief conclusion will follow.

2. Reputation and dealers' beliefs

2.1. Dealers' beliefs on other dealers.

We consider a dealership market where dealers know the identity of the other dealers who place the order with them, but this information is not accessible to the other market participants who are not parts of the transaction. This is a partial departure from the standard canonical models where anonymity is preserved (Kyle, 1985, Glosten and Milgrom, 1985), but allows us to study the issue of the informativeness on the dealers' type of the incoming order. Many results we will show are due to this feature.

The behavior of a trader is largely determined by his beliefs on the ability and degree of informativeness of the other market participants. This information depends on the trading features and institutional arrangements of the market. We focus on a dealership market where dealers can observe the identity of the people they trade with and the bid-ask prices posted by the other dealers. But they cannot see the size of the transactions intermediated by other dealers, nor the identities of the other dealers who originate them. This opacity generates asymmetric information as each dealer enjoys an informational advantage directly related to the trade he intermediates. This introduces heterogeneity and differences in their behavior.

In particular, we will focus on a particular source of heterogeneity: the one due to "reputation". We will loosely define reputation as the perception that each dealer has of the other market participants based on the information contained in the transactions he is part of.

In general, reputation arises with different agent types and incomplete information, and becomes economically important when types cannot be credibly signaled or learned except through the observation of actions. In a dealership market, it is the very process of trading that endows each dealer with information about the other market participants and allows him to develop beliefs concerning their ability, degree of informativeness and patterns of trading. That is, each trade not only reveals some information about future market conditions and/or liquidity shocks, but also helps the dealer to update his beliefs on the trader who has posted the order. For example, the fact that a particular dealer systematically purchases before an increase in prices or sells before a decline should imply that he has superior information or is bound to follow a particular trading strategy that led him to successfully time the market.

Given that this information is not available to the other dealers since it is entirely based on the information contained in the intermediated trade, dealers' beliefs on the other dealers are bound to differ from each other. This implies that each dealer has a different reputation vis-a-vis the other market participants, depending on his prior pattern of trades with them.

In a standard model with fixed individual characteristics, repeated interaction will eventually induce full revelation of the dealer type. That is "the sender of a signal reveals his type asymptotically" (Benabou and Laroque, 1992). However, if dealers' type is not fixed, but fluctuates over time, also "reputation itself may fluctuate up and down". This would be the case in a dealership market where reputation may be linked to the availability of short-lived information, that is information whose values depreciates over time.

Let's for instance assume that most of the information is related to short-term demand imbalances and that some dealer has prior information about them. This would indeed be the case if the dealer is at the same time intermediating a large fraction of the demand of terminal investors. For example, a dealer who places bids at the auction of Treasury bonds on behalf of institutional investors may use the demand schedule he intermediates to derive useful information about liquidity shocks. However, being this information short-lived, also the dealer type (i.e., informed or uninformed) is due to be short-lived. This implies that the types fluctuate over time, no full revelation takes place and different types can co-exist in equilibrium.

The fact that a dealer perceives the other dealers differently on the basis of the past history of trade he had with them induces him to assess differently the informational content of the incoming trade, depending on the basis of his beliefs on the dealer placing the incoming order. This implies that also his reaction will be different. That is, the dealer's overall propensity to trade and therefore impact on prices and volatility, will depend on how he perceives the other dealers (i.e. dealers' reputation) he is dealing with.

We will focus on two different aspects of how reputation is relevant. Let's start by considering a situation where a dealer perceives that on average the other dealers are better informed than he is. This is a classical case where adverse selection plays a role. Indeed, if dealers are risk neutral (Glosten and Milgrom (1985)) adverse selection would increase the required compensation to stand ready to trade (i.e., the bid-ask spread), while if the dealers are risk-averse (Spiegel and Subrahmanyam, 1996, Wang (1993)) adverse selection would increase the required risk premium and reduce the willingness to trade of the agents who think of being at informational disadvantage. Therefore, the trading behavior of a dealer convinced of the better ability/informativeness of the other dealers ("scared") would be different from the one of a dealer who enters the market confident that the other dealers are not more informed than he is ("confident"). The difference between the trades of a "scared" dealer and the trade of a "confident" dealer may be seen as a proxy for the degree of adverse selection in the market.

Let's now consider the trade of a dealer who has a good reputation with many other dealers - i.e. he is perceived as "smart" by the other market participants. In this case his trade will impact the market differently from the trade placed by a dealer whose characteristics are largely unknown or who is considered to be "dumb". Also in this case, the differential impact is related to adverse selection. Indeed, for analogous reasons, the trade of a smart dealer may impact the market more than the trade of a dumb dealer exactly because his reputation induces the other dealers to think of being on the wrong side of the transaction. That is, the perception that the market has of a particular dealer should also matter.

Therefore, both the priors that dealers have about the market (all the other dealers), as well as the priors on the specific dealers who place the order with them should affect the way they trade and the impact of their trade on market conditions (price, volume and volatility). Both these dimensions (scared vs. confident and smart vs. dumb) help to quantify the impact of informational asymmetry and adverse selection as described by the theory.

However, adverse selection is not the only channel through which reputation affects dealers' trade and their impact on market conditions. Reputation also affects the strategies that dealers enact to better exploit their information. Indeed, the informational content of the incoming order induces strategic behavior as each dealer realizes that the order flow reveals information and that by trading he may divulge this information to the market.

Let us suppose, for example, that a dealer receives an order to buy from a dealer who has a good reputation - i.e. someone who in the past has always bought before a rise in prices. The dealer has to decide how to exploit such information.

Given that changing the posted quotes he would partially reveal the information, he can decide to buy directly in the interdealer market, by placing orders with other dealers. Moreover, if he wants to hide his information, he should place the orders so as to minimize the informational impact of his trade. If, however, the dealer is not very confident about the quality of information contained in the order received, but he still believes it to have some content, he can decide to learn more about it. This could be the case if the dealer has noticed in previous trading with the "hitter", that the latter frequently, although not consistently, has correctly timed the market. Then, he may still decide to place orders directly with another dealer, just to observe his reaction to his trade and to learn from it. We could therefore say that he is "experimenting".

In the case of hiding as well as in the case of experimenting, the choice of the dealer to approach will therefore largely depend on the quality of the information received and on the beliefs on the other dealers to approach. That is to say, on the reputation of the dealer placing the incoming order and the reputation of the dealers to place orders with.

2.2. Testable implications.

For the empirical testing, we use these two dimensions - i.e. the one more related to adverse selection and the one more related to experimentation - to construct different groups of dealers and to assess their trading impact on market variables. That is, dealers are identified on the basis of their reputation and of the strategies they play. For instance, we classify dealers on the basis of their perceptions of the degree of informativeness of all the other dealers in the market. Then, we use these groupings to test out-of-sample the impact on prices, volume and volatility of these different dimensions of reputation and to assess their differential forecasting power in terms of these variables. It is important to notice that the fact that we first group the dealers in sample and then test their market impact out-of-sample, implies that there is no *a priori* link between the identification of the dealers and their explanatory power.

The generic null hypothesis is that of no differential impact based on reputation. The alternative hypothesis assumes that different classes of dealers can impact prices in a different way. Furthermore, we test whether there exists a class of dealers who systematically impact the market more than others. We will define these dealers as "salient dealers". These dealers are the ones whose trades have the highest forecasting power in terms of market variables (price, volume and volatility). This would correspond to finding some features in the different dimensions of reputation that play a more significant role in the market. Once dealers are properly grouped in classes (reaction-based and strategy based), the salient dealers are simply defined as the dealers whose trades have the highest forecasting power *out-of-sample.*

In particular, *cross-sectionally* we expect to be able to identify different types of trade defined in terms of the dealers who originate them. Furthermore, out of these classes we should be able to find the class of the salient dealers. That is to say, dealers whose trade is the predominant factor in the determination of stock volume and volatility.

A set of *time series restrictions* can also be derived on the basis of the fact that the very process of gradual revelation of information implies a difference between the short and long run. Such a difference depends on the speed with which information gets impounded into prices and, therefore, on the differential impact of the different types of dealers. In particular, we expect that the quicker the information gets impounded into prices - i.e. the stronger the short-term impact - the lower future volatility and volume would be. That is, if prices swiftly impound the new information at time t, volatility and volume at time $t + \Delta t$ minutes will be less sensitive to such information.

3. The market and the dataset

The market considered here is the Italian Treasury bond market. Along with the FX market, this market shares the important feature that information is more about non-fundamentals-driven shifts in demand than about fundamentals (Ito, Lyons, and Melvin (1998) and Cao and Lyons (1999)). In terms of the distinction put forward by Cao & Lyons (1999), we can define this information as payoff-irrelevant information. That is, information that is not related to the fundamentals (e.g, dividends, level of interest rates), but to anything else (e.g., inventory information). That is, the uncertainty that affects prices is not related to the payoffs of the traded asset.

This sets this markets aside from the equity market where information is mostly about fundamentals. The fact that, in our case, information is mostly payoff-irrelevant and more "dealer-dependent" (e.g., in case of inventory rebalancing) suggests that it is possible to directly infer the reaction of the dealers to information by observing their reaction to order flows. Until now the lack of data covering the whole market has prevented this type of analysis.

The Italian market is a centralized and regulated inter-dealer market, where all the transactions are concentrated.[3] This allows us to observe the behavior of the market as a whole. This stands in stark contrast to the other Treasury bond markets, including the US, where the transactions are mostly over-the-counter, and therefore any analysis would have to be limited to a subsection of the market.

The market (Mercato Telematico dei titoli di Stato, M.T.S.) is a screen-based market (for detailed description see Banca D'Italia (1994), Banca D'Italia (1995)). Transactions take place between 9.00 a.m. and 5.00 p.m. Three types of intermediaries trade on it: ordinary dealers (around 360), ordinary market makers (40) and primary dealers or specialists (16). They are mostly banks, investment firms and insurance companies. Dealers can only place orders with the market makers and cannot post bid and ask prices. Market makers are dealers who commit themselves to post continuously a bid and an ask price. They can place orders with other market makers. The specialists are dealers subject to tighter trading requirements. To qualify as a specialist, a dealer has to trade a minimum percentage of each type of bond on the secondary market [4] and to purchase a minimum number of bonds at each auction. In exchange for more binding trading requirements, he enjoys particular re-financing benefits and is entitled to borrow at an advantageous rate at the discount window of the Bank of Italy. Inter-dealer trade represents 75-80% of the overall trade.

Each trader (ordinary dealer, ordinary market maker and primary market maker) has access to a screen where he can observe the bid and ask prices the market makers (both primary and ordinary) post, and the maximum number of bonds they commit themselves to trade. Market makers are not anonymous.[5] That is, the name of the market maker appears on the screen next to the bid and ask prices he is posting. Each

[3] Some trades also take place in the Stock Exchange, but these represent a very limited fraction of the overall total (less than 10%). Furthermore, all the trades in the Stock Exchange take place at prices that reflect the ones set in the inter-dealer market (Banca D'Italia (1994)).

[4] 1% of the total number of transactions in most liquid bonds and 3% of the less liquid ones.

[5] This was true for the period covered by this study. Later on (June 1997), quotes became anonymous.

market maker knows the identity only of the counterpart he is trading with. This means that each market maker knows the counterpart who has placed an order with him, as well as the other counterpart he is going to place an order with. No market participant (ordinary dealer, market maker or primary market maker) knows the identities of other market participants involved in a transaction in which he is not involved.

The transactions are executed at the posted price. When a transaction takes place, the name of the market maker "hit" blinks, signaling to the market that he is trading and the price at which this transaction takes place. The volume of the transaction is never revealed, except in the rare case where a market maker receives an order equal to the maximum number he has committed himself to trade. In this case, he automatically withdraws from the market for a period not exceeding 60 seconds. This withdrawal is the only signal the market receives about the size of the transaction.

Analogously to the FX market described by Lyons (1995), the slow diffusion of information via interdealer trade is facilitated by the absence of trade reporting. 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 also on a specific page by Reuters.

All the transactions are settled through a settlement 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 market makers meet the requirements in terms of continuous posting of bid-ask prices, the minimum number of transactions executed per category of bond and the size of the bid-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.

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

The dataset contains all transactions from 29 September 1994 to 28 February 1996 for all listed bonds. They total 1,393,437 transactions. For each transaction, we have the following information: the time at which the transaction is executed, the size of the transaction, the price and the name of the counterparts and the identity of the dealer who originated the transaction. This allows us to distinguish the trades that have been originated by the market makers from those received from other dealers. The descriptive statistics of the data are reported in Table 1 (Panels A, B and C). On average, each market maker intermediates 2.2% of daily volume. It is also important to note that there is very little dispersion in terms of volume of transactions. More than 88% of transactions have standard size (5 bln. lire in face value). Only 0.4% of all transactions are in excess of 20 bln. lire. To avoid issues of strategic interactions between the primary and the secondary market, for each bond we have omitted the days when such a bond was being auctioned off.

The fact that in the market 88% of trades are the standard size and only rarely does a market maker receive an order equal to the maximum he is willing to trade show that the average order is almost always less that the maximum. In other words, the maximum is almost never of the standard size.[6] It is interesting to note that this feature makes this dataset particularly well fit for analysis for theories of discreteness and barganing efficiency.

[6] Whereas we do not have descriptive statistics about posted depth - i.e. the maximum number of bonds the dealer is willing to trade at the specified quote - of the market, casual observations of Reuter screen and conversations with the traders confirms that the depth is normally within 10-20 standard trade sizes.

Transactions will be grouped into *passive* and *active* ones. A *passive* transaction is one that the market maker receives when someone hits his bid or ask price. An *active* transaction is one that the market maker originates by placing orders with other market makers. Active and passive trades would correspond to Lyons' (1995) definition of outgoing and incoming trades respectively.

4. Short-lived information and dealers

In order to define the impact of different classes of dealers we have first to define these classes. Therefore, we first identify dealers in sample on the basis of their beliefs on the degree of informativeness of other market participants and in terms of the way they strategically condition their choices on the basis of them. Then we test out-of-sample the impact of their trade on price, volatility and overall volume and test whether different classes of dealers have different impacts and whether the dealers who should have the strongest impact a priori are really the ones who affect prices the most.

We assume that information is short-lived, that is its value is reduced as time passes by. This fits the type of market where most of the information is not related to the fundamental as to some temporary imbalances in the demand. These imbalances provide an informational advantage to the dealers who intermediate such a demand. However, this advantage is due to disappear very quickly as these temporary imbalances are absorbed by the market. This implies that this type of information is only valuable for a dealer for trading purposes for a short time.

4.1. A definition of information

For simplicity we will use the term dealer to define all the market participants (ordinary dealer, market maker and specialists). The informational content of the incoming trade can be inferred by looking at the dealer who has originated the trade. "From perhaps bitter experience dealers learn to identify likely information traders" (Cox and Rubinstein (1985)). That is, each dealer learns about the degree of the informativeness of the other dealers he is trading with by simply looking at the behavior of prices in the period following the transaction he executed 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 therefore refer interchangeably to the informational content of trade and to the degree of informativeness of the dealer originating it.

Their beliefs are updated on the basis of the order flow. In order to determine the degree of informativeness, we look at the changes in prices of the same bond in the 5 minutes that follow each transaction. In particular, we estimate:

$$\Delta P_{k,t+5} = \gamma_{ij} T_{ijk,t} + \varepsilon_{ijk,t+5} \tag{4.1}$$

in a pairwise relation versus all the other i dealers *for each individual bond k.* We define $T_{ijk,t}$ as the (signed) orders received by the *i-th* dealer from the *j-th* dealer for the *k-th* bond at time t. $\Delta P_{k,t+5} = (P_{k,t+5} - P_{k,t})$ is the change in the price of the *k-th* bond in the 5 minutes following the receipt of such an order.[7] We use the actual transaction prices and not mid-quotes. That is, we use the actual price at which each transaction is executed ($P_{k,t}$) as well as the transaction price of the same bond in the following 5 minutes.[8]

[7] $\Delta P_{k,t+5}$ 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.

[8] In particular, we use actual prices in the next 5 minutes. So for P_{t+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

Equation 4.1 is estimated for each dealer at the beginning of each day. Each time the data comprises all the orders the dealer has received in the previous 10 days and all the ensuing changes in prices. A 10 day window has been chosen on the basis of the trade-off between the accuracy of the estimation and the time-varying dimension of the estimate due to short-lived information. Indeed, the longer the window is, the better the power of the econometric estimate is. However, this conflicts with the fact that information is short lived and therefore the degree of informativeness of the dealers changes over time. 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, we recognize that the 10 days windows is a rough rule of thumb and we therefore performed extensive robustness tests with different windows.[9]

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.

The coefficient γ_{ij} represents the degree of informativeness of the specific *j-th* dealer who is placing the order, as perceived by the *i-th* dealer. A significant value of γ_{ij} implies that the dealer is informed. The greater the value of the coefficient, the higher the degree of informativeness of the dealer is, and the greater the informational content of the order received by the dealer.[10] A positive value of γ_{ij} means that the *ith* dealer has consistently bought (sold) from the *jth* dealer before an increase (decrease) in prices.

It is worth noting that, given that we use transaction prices, bid-ask bounces are in the returns. This would induce negative serial correlation that would make it more

the interval is used. In the case no transaction exists, $P_{t+5} = P_t$.

[9] The results agree with the ones reported in the text and are available upon request.

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

difficult to detect information effects.[11] This induces to consider our tests are more conservative.

In Table 2, Panel A, we report the results of the estimation of equation 4.1. The dealers who are perceived as being more informed, both in terms of value of the coefficient (γ_{ij}) 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.

How does this information behave over time? In other words, is it possible to quantify the probability that a dealer who is informed at t is still informed at $t + \Delta t$? In order to address this question, we calculate the transition probability matrix of γ_{ij}, i.e. the probability that γ_{ij} is statistically significant at time T, conditional on it being statistically significant at $T - t$ before.

In Table 2, Panel B, we report the transition probability matrices for different levels of γ_{ij} and of the statistical significance of such a variable (*p-value* of γ_{ij}). Dealers are grouped in classes and the transition probability matrix is defined as the probability of moving from one class to another, conditional on having belonged to a particular class 10 days before. We consider 5 classes. The dealers whom the dealer is 90% confident are able to successfully time the market (buy before increase in prices and sell before a reduction in prices). This class comprises all the dealers who have a $\gamma_{ij} > 0$ and $p - value \leq 0.1$. We define them as "consistent market timers". The dealers whom the dealer believes to be able to successfully time the market with confidence between 50% and 90% ($\gamma_{ij} > 0$ and $0.1 < p - value \leq 0.5$). We define them as "market timers". The dealers whom the dealer has low knowledge about ($p - value > 0.5$).

[11] The fact that we the median time between transactions is 13 seconds only partially alleviates the problem as the longer the inter-transaction time, the smaller is the half spread relative to the total returns.

We define them as "the rest". The dealers whom the dealer is very confident ($\gamma_{ij} < 0$ and $p - value \leq 0.1$) will sell before increase in prices and buy before a reduction in prices. We define them as "consistent contrarians". It is worth noting that this is not the standard definition as these traders are ex-post losers. The dealers whom the dealer believes to follow contrarian strategies with a confidence between 50% and 90% ($\gamma_{ij} < 0$ and $0.1 < p - value \leq 0.5$). We define them as "contrarians". The last two classes can be thought of as having institutional constraints. For example, if we assume that the dealer has a set of stop 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.[12] However, it is worth noticing that the number of contrarians is small. In general, the average fraction of positive γ_{ij} for each trading day is around 80.1%, while its median value is 82.0%. As a robustness check, we run the estimates reported below for the case of a positive γ_{ij}. The results do not differ from the ones reported.[13]

Reputation, even if it shows a certain degree of persistence, is not stable but changes over time. In particular, while a low reputation ($p - value > 0.5$) tends to persist over time, high reputation has a much shorter life. The high reputation ($p - value \leq 0.1$) of a certain type ($\gamma_{ij} > 0$) has a half life of approximately 2.5 days. This suggests a relative fast rate of depreciation of the degree of informativeness of the dealers. This relative lack of stability may be useful to address the issue of whether steady states in dealer markets of this type are more likely when informational advantages are redistributed frequently.

We use this definition of information to classify active trades into *informed* and *uninformed* trades, depending on the degree of informativeness of the dealer who places

[12] In general, the fact that the behavior of these dealers is statistically significant suggests that they play consistent strategies, even if we are not able to identify why they play such strategies.

[13] They are available upon request from the authors.

the order (originating trade) prompting the market maker to react by placing an order with another market maker. That is, informed trades are the ones originated by a market maker who has been just "hit" by a dealer whom he deems to be informed, while passive trade is the one originated by a market maker after having been hit by a dealer whom he does not think to be informed.

4.2. Classifications of dealers

We can now proceed to classify dealers. A first classification identifies dealers in terms of their perception of the degree of overall market informativeness. This measure captures the average degree of informativeness that the dealer believes the other dealers surrounding him have. That is, it quantifies the *size of adverse selection he perceives to be facing.* For each dealer (i) we construct a statistic (h_i) defined as the sum of the degree of informativeness of all the other (j) dealers in the market as perceived by him. That is,

$$h_i(t) = \sum_{j \neq i} \gamma_{ij}^2(t), \tag{4.2}$$

where $j = 1, .., i-1, i+1, ..N$ and $i \neq j$. Then, for each day t we rank dealers into three categories based on $h_i(t)$. The top 25% are classified as "scared", the bottom 50% are termed "confident" and the rest are referred to as "averages".[14] Scared are dealers who enter the market at day t with the perception that most of the other dealers are well informed or capable. On the contrary, confident are dealers who have developed a belief that most of the other dealers are not well informed - or at least, in their past history

[14] The reason we chose such a cut-off is due to the uneven trade size of the dealers. Indeed, many dealers trade very little. If we considered three groups with equal number of dealers, we would find that the third group would most likely be insignificant in terms of trading volume. We therefore proceed as follows. First we find the constant number of dealers that would provide three classes with approximately equal size in terms of trading volume across the entire period of our sample. Then we use such a number as a cut-off to construct the classes.

of trade with the dealer, they have not shown any significant timing relationship with respect to market prices.

A second classification deals with the market consensus beliefs. This measure captures the perception of the overall market about the ability of a specific dealer. This gauges his reputation across all the market participants. For each dealer (i) we construct a statistic (k_i) defined as the sum of the beliefs that all the other dealers have on him. That is,

$$k_i(t) = \sum_{j \neq i} \gamma_{ji}^2(t), \tag{4.3}$$

where $j = 1, .., i-1, i+1, ..N$ and $i \neq j$. As in the previous classification, we sort the dealers daily on the basis of the value of $k_i(t)$. We then divide the dealers into three classes: the top 25% of dealers, the bottom 50%, and the rest. We call the first "smart", the second "dumb" and the third "averages". A smart dealer is someone on whom an implicit consensus among the other dealers has been established. His trading patterns in the previous days have persuaded the other dealers that he has timing skills. Therefore, his trade should have a deep impact. On the contrary, the dumb is a dealer who, by general consensus, does not have timing skills. Therefore, his trade should have the lowest impact.[15]

In Table 2, Panel C, we report the probability of dealer being in *ith* category conditional on the dealer being classified as belonging to the *jth* class 10 days before. We

[15] As a robustness check the previous two classifications have also been built by using the weighted sum of the γ_{ij}^2, where the weights are the probability values generated by the estimation of equation 4.1 and providing the degree of significance of the estimates of $\gamma_{ij}s$. The results agree with the ones reported.

Furthermore, we also constructed our classifications by using the absolute values of γ. The results did not differ so we chose to have all the estimations based on squares.

can see that a dealer has less than 50:50 probability of being continuously classified in the top category. Also, it is interesting to notice (Table 3, Panel D) that there is a monotonic dependence between both $h_i(t)$ and $k_i(t)$ and volatility.

The aforesaid classifications do not involve dealer's strategic behavior. We now proceed to consider a classification where dealers are explicitly defined on the basis of their strategic reaction to the degree of informativeness of the other dealers. The starting point is the intuitive observation that each dealer realizes that by trading he may impact on the market and release his information. Therefore, he may wish to act strategically, by selectively choosing the dealer whom to place the order with.

If the dealer perceives the information he has acquired by trading to be of good quality, he may try to exploit it by placing orders with a less informed dealer. This would also reduce the amount of information disclosed to the market. Indeed, while informed traders already have an information set which allows them to exploit the information contained in the incoming trade, the less informed ones cannot fully appreciate the informational content of the order placed with them.

If, on the other hand, he is not confident about such information, he may try to assess its quality by observing the reaction of the other dealers to his trade. In the former case, the dealer will try to *hide* his information, in the latter case he will try to *experiment* to better learn the true value of the information.

We can therefore group dealers according to the way they react to orders received: the dealers who try to hide the information they receive would place orders with dealers less informed than those who have placed orders with them and the dealers who try to assess the quality of their information would place orders with dealers more informed than those who have placed orders with them.

In particular, each day and for each dealer we rank the other $n-1$ dealers in terms of the confidence that such a dealer has on their being informed. We then group all the dealers in the 5 classes defined before (i.e., consistent market timers, market timers, consistent contrarians, contrarians and the others). For each class we calculate the number of times the dealer has directly placed orders with it. Then we estimate:

$$y_{jt} = \beta x_{jt} + \delta \mathbf{C}_t + \varepsilon_{ijt}. \tag{4.4}$$

where, y_{jt}, $j = 1, ..., 5$ is the sum of trades the (ith) dealer places with another dealer belonging to class j standardized by the overall trades that the dealer places with other dealer belonging to class *j,* x_{jt} is the difference between the average reputation (degree of informativeness, γ_{ij}) of the dealers belonging to class j and the reputation of the dealer placing the originating trade. Finally, $\mathbf{C}_t$ is a vector of control variables. [16]

Dealers are then grouped into three classes on the basis of the value of β [17]*:* those who place orders with dealers who are more informed than the dealers who have "hit" them, those who place orders with dealers who are less informed than the dealers who have "hit" them and thirdly, the rest. We call the first "skeptic", the second "sneaky" and the third "averages". Sneaky dealers can be thought of as dealers who try to hide their information, while skeptics can be considered as dealers who try to learn the quality of the information contained in the orders they have received by assessing the reaction of the dealers they approach. That is, they place orders with other market makers just to see how they react. If the informational content of the incoming trade is valuable, changing the bid-ask quotes would reveal such information to entire market. Conversely, keeping the quotes unchanged and placing orders with other market makers allows

[16] They include market volatility at the time, the amount of trade that the market maker is generating exogenously by changing the bid and ask quotes, standardized by the overall trades that the market maker intermediates in the same period, and the overall sum of trades that the market maker places with other market maker belonging to class *j,* standardized by the overall trades that the market maker directly places with other market makers in the same period. These ratios as well as the dependent variable are expressed in logarithm form.

[17] The values of the βs (and *t-statistics*) are 7.57 (3.26) for the market makers in aggregate, -25.63 (-3.66) for the skeptics, 2.19 (0.81) for the averages and 27.27 (18.28) for the sneaky market makers. The full estimates are available upon request from the authors.

the market maker to exploit the anonymity of the market to exploit his information. Therefore, a market maker uncertain about the informational content of the incoming trade would place the order with another (possibly more informed) market maker in order to assess his reaction. By looking for clues in the observable spread response, he would in fact experiment. Finally, *averages* are the dealers who do not pursue an active strategy. [18]

It is worth noticing that our measure of informativeness includes also the counterparts who are negatively correlated with returns. While this makes sense from an informational perspective, it may seem puzzling from a purely microstructure one. We therefore assessed the robustness of our results in the case we restrict our sample to the cases where $\gamma_{ij} > 0$. In this case, no change occurs in the identification of the skeptics, while two additional market makers are classified as sneakies. Analogously, in the first reaction-based classification, in 80% of the cases (daily identifications) dealers belong to the same classification they had been assigned to when no restrictions had been placed on γ_{ij}, while in the second reaction-based classification, in 96% of the cases dealers are classified the same way as they had been when no restrictions had been placed on γ_{ij}. [19]

[18] Unlike the previous classifications which were based on a time-varying variable such as reputation, this classification is based on strategies which are related to the characteristics of the market maker playing them (e.g. risk aversion, type of demand intermediated). Therefore, given that we expect the classification to be stable over time, we will define it over the entire sample. However, in order to be sure that it is not affected by any "in-sample bias", we apply a cross-validation technique. That is, we split the sample into odd and even days and then we identify the dealers on odd days and run all our estimates on even days, using the classification of the dealers found in the odd days. Furthermore, we also test the robustness of the classification itself. For this purpose we classify the dealers separately using either odd or even days, and then we check the consistency of the two classifications. The two approaches classify the dealers in the same way.

[19] Also, estimates of the main specifications based on the new classification based only on $\gamma_{ij} > 0$ are consistent with ones provided in the text. They are available upon request from the authors.

5. Empiric l evidence of differential impacts of trade

Once different classes of dealers have been constructed, we move on to assess the differential impact of the trade of dealers belonging to such classes. While classes have been constructed in sample, we estimate the market impact out-out-sample. In the following we will describe the main results referring to the tables for further details. It is worth noticing that all the tables contain test statistics designed to assess the statistical significance of the difference in impact across different classes of dealers.

5.1. Preliminary tests

In order to test whether these classifications deliver statistically significant differences in terms of the impact of trades we run a preliminary *t-test*. It compares the volatility of different types of trade in the intervals immediately following the originating transaction. The aim is to see which class of dealers generates the trade that has the highest impact on volatility. A pairwise comparison between trades originated by different dealers should give a preliminary answer to the question of whether, *in the short run*, the type of intermediary placing the order makes a difference in terms of market impact.

In order to implement this we select all the transactions that have an informational content (i.e. levels γ_{ij} and their statistical significance) and group them according to the class of dealer that has received them and then calculate the volatility on the same bond in the two 10-minute intervals following the originating trade. Volatility has been constructed on 10 minute windows starting after the originating transaction. In particular, for a transaction taking place at time t, the intervals are defined as [t,t+10min] and [t+10min,t+20min]. This generates a series of observations on volatilities which are identified on the basis of the dealer who has received them. In Table 3, we report the statistics of volatility for the different classes of dealers, according to the three classifications (Panels A, B and C) and the *t-tests* on the pairwise differences among them.

The results give a clear ordering of the effects. In particular, they show that, *in the short run,* the classes of dealers who have the strongest impact are the scared, the smart and the skeptics. For instance, in the 10 minutes following a trade originated by a smart dealer, volatility is, on average, 27% higher than in the 10 minutes following a trade originated by a dumb dealer. The difference between the two is strongly statistically significant (*t-statistic* equal to -12.52). Also, in the 10 minutes following a skeptic-originated trade, volatility is, on average, 19% higher than in the 10 minutes following a trade originated by a sneaky dealer. The difference between the two is strongly statistically significant (t-statistic equal to -8.47). This fits with our hypothesis since the sneakies, by hiding their information, tend not to affect the market in the short run. The converse is true for the skeptics. By experimenting, they allow part of their information to be incorporated into prices. Given that the informational impact of their trade is very low, prices adjust slowly and volatility rises.

In order to assess the robustness of our results to the way we group dealers into classes, we also report the results of WLS estimate of the regression:

$$\sigma_{k,t} = \alpha_0 + \alpha_H H_{it} + \boldsymbol{\beta}\mathbf{C}_{k,t}, \tag{5.1}$$

where $\sigma_{k,t}$ is the volatility of the kth bond at time t and $H_{it} = h_{it}$, k_{it} as defined in Eq. (4.2) and Eq. (4.3) for Classifications 1 and 2 correspondingly (Table 3, Panel D). That is, we directly test the impact of the indexes we used to build our classes. This should help us to control for any possible bias induced by the choice of the cut-off points in the construction of the classes. $\mathbf{C}_{k,t}$ represents lagged control variables. Is is a vector containing measures of volatility over the prior 10 minutes and prior 1 hour. These variables are required as volatility is persistent and is a known driver of inventory adjustment trading. Therefore, its omission may significantly bias our estimates.

The results show a strongly significant positive relationship between volatility and the degree of adverse selection of the dealer (h_{it}) or the perceived informativeness of the originating dealer (k_{it}). [20]

We therefore have the first evidence of the classes of dealers who are "salient" in the short run. We can now test the role played by trades originated by salient dealers and their differential impacts with respects to other classes of dealers more formally, by focussing on the cross-section and time-series implications of it.

5.2. Reputation and market depth

A first test considers the instantaneous market impact of the trade originated by the different types of dealers. The null hypothesis is that there should not be any significant difference in the market impact of the different types of dealers. In order to estimate the price impact we consider two specifications: the one suggested by Glosten and Harris (1988) and that developed by Madhavan and Smidt (1991). These procedures relate the change in prices at transaction time with the inverse of the market depth as derived in a Kyle-type model. We therefore estimate:

$$\Delta p_{i,t} = \lambda_i q_{i,t} + \lambda_i W_i q_{i,t} + \psi(D_{i,t} - D_{i,t-1}) + \varepsilon_t \tag{5.2}$$

for the procedure of Glosten and Harris and

$$\Delta p_{i,t} = \lambda_i q_{i,t} + \lambda_i W_i q_{i,t} + \frac{\psi}{\pi_i} D_{i,t} - \psi D_{i,t-1} + \frac{\gamma}{\pi} I_{i,t} - \gamma I_{i,t-1} + \eta_t \tag{5.3}$$

for the case of Madhavan and Smidt, where $\lambda_i \equiv \frac{\alpha_i^{-1}(1-\pi_i)}{\pi_i}$ and α_i represents the reaction of order flows to prices.[21] Here $\Delta p_{i,t}$ is the change in price at time t of a transaction

[20] We also run robustness check with $\widetilde{H}_i = H_i/max_i(H_i)$. The results are similar to the ones reported.

[21] In particular, $q_{i,t} = \alpha_i(\mu_{i,t} - p_{i,t}) + z_{i,t}$, where $z_{i,t}$ is the liquidity component of trading, $\mu_{i,t}$ is the mean of private information and, $\mathrm{p}_{i,t}$ is the price and $\mathrm{q}_{i,t}$ is the quantity traded. The estimation of the reduced form equation 5.3 requires the use of the Box and Jenkins methodology. For a more detailed description of this approach we refer to Madhavan and Smidt (1991) and to Brennan and Subrahmanyam (1995).

originated by a dealer belonging to the *ith* class and $q_{i,t}$ is the signed order flow at time t of the trade originated by such a dealer. $D_{i,t}$ denotes the sign of the order placed by the dealer belonging to the *ith* class at time t ($+1$ for a buyer-initiated trade and -1 for a seller-initiated trade) and $D_{i,t-1}$ is the sign of the order immediately preceding the order placed by the dealer belonging to the *ith* class at time t. W_i is a dummy that accounts for the institutional differences within each class. It takes the value 1 if the transaction is originated by an ordinary market maker and 0 otherwise. $I_{i,t}$ is the inventory of the *ith* dealer at time t. This allows us to test whether the impact of trade is significantly affected by the institutional classification.[22]

In the case of Glosten and Harris, the error is assumed to be white noise, while in the case of Madhavan and Smidt the error follows an MA(1) process. The subscript i refers to the category considered within each classification (e.g., $i = \{scared,\ average,\ confident\}$ for the first classification. Both equations 5.2 and 5.3 are estimated by pooling all the observations and using dummies to differentiate on the basis of the dealers originating them.[23]

In Table 4 we report the estimates of equations for different classifications of the dealers and the χ^2 of the Wald tests of the hypothesis of equality of the coefficients

[22] The inventory of the *ith* dealer at time t on the *kth* bond is constructed as $I_{i,t} = \sum_{s=0}^{t-1} Q_s$, where Q_t are the market makers' buys/sells at time t and $s = 0$ is the starting point used to construct the inventory. This is the same methodology applied by Madhavan and Smidt (1991). The auction allocations are included at the moment of official announcement of the results.

[23] In order to assess the robustness of the results to the way dealers are grouped into different classes, we estimate Equations (5.2) and (5.3) with $\lambda = \lambda(1 + \lambda_1 H_{it})$, where $H_{it} = h_{it}$, k_{it} as defined in Eq. (4.2) and Eq. (4.3) for Classifications 1 and 2 correspondingly. That is, we directly test the impact of the indexes we used to build our classes. This should help us to control for any possible bias induced by the choice of the cut-off points in the construction of the classes. We also tried specification where the H_{it} is normalized to its maximum value $\max_i(H_{it})$ over the course of the given day. In both cases, the results (not reported) are consistent with the reported ones. They are available upon request from the authors.

across classes of dealers within each specification. [24]

The results strongly support our working hypothesis of differential impacts of the different classes. In particular, the salient dealers (scared, smart and skeptics) have the strongest impact (respectively 0.000632, 0.000526 and 0.000914, for the Glosten-Harris specification).[25] Furthermore, the differential impact is statistically significant in all the classifications with a *p-value* less that 0.01. It is interesting to notice that in the cases of the reaction-based classification (i.e., confident/scared and dumb/smart), being an ordinary market maker significantly increases the market impact of both the confident and the dumb, while it does not affect the one of the scared and smart. Therefore, it does not alter the differential impact between classes defined just on the reaction-basis.

This may be explained by the fact that the scared and the smart are already the dealers whose impact is the strongest. Therefore, the institutional classification does not significantly affect the impact. On the contrary, the confident and the dumb affect prices less. If the blunter impact is due to a strong heterogeneity within class, the further breakdown on the basis of the institutional classification helps to better define the impact of sub-classes.

More complicated is the story in the case of the strategy-based classification. Indeed, the dummy that accounts for the institutional classification provides additional explanatory power for both sneakies and skeptics. The sign of the dummy indicates that ordinary market makers are more inclined to exploit directly the informational impact of trade without experimenting. The Wald test of the difference of impact between

[24] We also estimated the same specifications disaggregating the data into informed and uninformed trade. The results (not reported but available upon request) show that informed trade has a statistically higher impact that uninformed trade in all the three classifications.

[25] Whereas we do not have descriptive statistics about posted bid-ask spread of the market, casual observations of Reuter screen and conversations with the traders report an average bid-ask spread of approximately 3 bp. The market impact for $\lambda = 0.000632$ is approximately 0.3 bp for standard transaction size.

ordinary market makers-sneakies and ordinary market makers-skeptics is rejected at all conventional levels of significance[26].

Finally, it is worth noting that, while inventory seems to play a role in affecting the market impact, such an impact is not affecting the results. Indeed, both the Glosten-Harris specification (not containing inventory) and the Madhavan-Smidt one (containing inventory) provide analogous results. Furthermore, as an additional check we also estimated the Madhavan-Smidt specification without inventory and the results agree with the ones reported.[27]

The results show that the impact of informational variables is indeed strong and significant. The greater the extent to which the dealer is scared, the larger is the price impact of the trade (both λ and λ_1 are positive and strongly statistically significant). Similarly, the higher the degree of perceived informational advantage of the initiating dealer, the stronger is the price impact of the trade. These results suggest that, in the very short run, the market is less deep (higher λ) when the trade has been originated by an salient dealer. That is, reputation influences the way dealers' trades impact the

[26] More precisely, we test the hypothesis of $\lambda_{SNEAKY} + \lambda_{SNEAKY}W = \lambda_{SKEPTIC} + \lambda_{SKEPTIC}W$. The resulting χ^2 is 17.65 and 24.69 for Glosten and Harris and Madhavan and Smidt specifications correspondingly.

[27] The results are available upon request.

market.[28]

5.3. Rep tation and pri e impact over time

5.3.1. Short term horizon

The next step involves the analysis of the price impact over time. We test whether different types of trades have different impacts on overall trading volume and volatility

[28]It is possible that the small trade impact, coupled with scarcity of transactions, would make these results statistically significant, but economically irrelevant. We therefore, endeavored to account for the series of price impacts against the spread as opposed to the price impact of a single transaction, by re-estimating equations 5.2 and 5.3 with dummies that account for the fact that there was either at least one transaction intermediated by the same market maker in the same bond in the previous minute or at least two transactions intermediated by the same market maker in the same bond within the previous minute. The results (not reported, but available upon request) are consistent with the ones reported. In particular, the cumulative impact in the case the same dealer is intermediating more than one transaction in the previous minute is about 1 bp that is three times more than the one estimated by considering a single transaction.

in the periods following the transactions.[29] We estimate:

$$mv_{k,t+\Delta} = \alpha + \sum_{j=1}^{N} \beta_a^j \mathbf{X}_{a,k,t}^j + \sum_{j=1}^{N} \beta_p^j \mathbf{X}_{p,k,t}^j + \gamma mv_{k,t-10} + \delta \mathbf{C}_t + \varepsilon_{k,t} \tag{5.4}$$

where $mv_{k,t}$ is the market variable under consideration (overall trading volume $V_{k,t}$ or volatility $\sigma_{k,t}$ of the *kth* bond) and $\mathbf{C}_t$ represents a vector of control variables.[30] $X_{a,t}^j$ and $X_{p,t}^j$ represent, respectively, the active and passive trades [31] of a dealer who belongs to the *jth* category. That is the trades they have respectively originated and received,

[29] For robusteness, we also consider two alternative specifications. The first one is based on on clock time. While an analysis based on transaction time has the benefit of capturing the varying degrees of significance that high and low volume periods have, it nevertheless suffers from the fact that it eliminates all the information contained in the periods when no transactions take place. This amplifies the informational content of the periods when the trades are lumped together. We therefore re-estimate equation 5.4 on the basis of clock time and with a the variables defined not on levels but on rates of changes of trading volume. We do this in order to be able to run a proper horse-race between trades originated by different types of dealers. Indeed, using rates of change makes the coefficients more homogenous and purge them of the effects due to differences in the number of trades.

The alternative approach is to use a GARCH structure where the errors of equation 5.4 are modelled in the following way: $\varepsilon_{ik,t} = \rho \varepsilon_{ik,t-1} e^{(\frac{-\Delta t}{\tau})} + \nu_{ik,t}$. Here, 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. Given that the results of these two alternative specifications agree in general with the one reported, we will not report them. They are available upon request from the authors.

[30] They include dummies to control for the specific microstructural effects due to the beginning and end of the day (the first and last 60 minutes of the trading day) as well as the dependent variable lagged for the previous 60 minuts (*t-60*). Also, to test for the robustness of the results, we estimate a specification with both the the value of the dependent variable in the previous 10 minutes, as well as its average value in the previous day. Furthermore, we also include the value of the inventory of the particular class of dealers as specified in the existing literature (Madhavan and Smidt, 1991, Hansch, Naik, and Viswanathan (1998)).

[31] Trades are defined as the sum of the absolute values of all the transactions originated by the dealers belonging to the particular class under consideration.

or, using Lyons' (1995) definition, outgoing and incoming trades. The superscript j refers to the category considered within each classification (e.g., $j = [scared, average, confident]$ for the first classification). We consider the two reaction-based classifications, the strategy-based classification and the institutional classification.

The market variables (volatility and volume) are computed for each $k-th$ bond, for 10 minute intervals, so as to be homogeneous with the time interval of the specification tested. That is, for a transaction taking place at time t, volatility and volumes are constructed for 6 intervals, each of 10 minutes, after the time of the transaction (i.e., [t,t+10], [t+10,t+20], [t+20,t+30], [t+30,t+40], [t+40,t+50] and [t+50,t+60]). We use a panel specification, considering each single transaction as a separate event, identified on the basis of the dealer who has placed the order. All the transactions are stacked together.[32]

Table 5 illustrates the results showing the impacts of active and passive trade on both volume and volatility reported for the estimates based on transaction time. They are broken down into the four classifications in Panels A, B, and C. The impact on aggregate market volume and volatility are reported, in the upper and lower part of the tables respectively. The results strongly support our hypotheses.

First, the reaction of volume and volatility to active trade is very different from the reaction to passive trade. Active trade affects volatility or volume more strongly than passive trade. This holds across the different classes and for the different time intervals. Furthermore, Wald tests reported in Table 5 show that the difference in impact between active and passive trade is always statistically significant. This holds

[32]In the case of clock time, we aggregate trades every 10 minutes, separating them according to the class of dealers that has placed the order. That is, we consider intervals equal to: $t = 9:00, 9:10, ..., 16:50, 17:00$, $T = 0, 10, 20, 30, 40, 50, 60$ min, where t represents clock time. In this case, we do not add inventory among the explanatory variables as the aggregate inventory of an entire class of dealers has scarce signicance.

for all the classifications and for both volume and volatility.

Second, the way that active trade impacts on volume and volatility depends on the type of dealer who is placing the order. Trade originated by salient dealers' has a stronger impact. This holds across classifications. In particular, a smart dealer impacts on volume and volatility more than a dumb one. A scared dealer impacts on volume and volatility more than confident dealers and a skeptic has a stronger impact than a sneaky one. This taxonomy of effects is consistent over time. That is to say, the salient dealers do consistently have a stronger impact in the short term as well as in the long term. Furthermore, Wald tests reported in Table 5 show that the difference in impact of the between trades originated by different classes of dealers is always statistically significant. This holds for all the classifications and for both volume and volatility.

Third, the effects of trade differ over time. The effects of trade on both volume and volatility are always positive for the first 20 minutes following the trade, then become insignificant, and finally turn strongly negatively significant in the period between 30 and 50 minutes after the trade. These results seem to imply that the process of releasing information has a time-varying pattern that is linked to the informational content of trade.

This suggests that trade releases information, and this produces short-run effects that are different from those of the long run. *In the hort run*, trade, by channelling more information but only to a sub-set of the traders, increases information asymmetry and raises volume and volatility. *In the lon run* ("at the steady state"), the additional information is completely impounded into the prices (Wang (1993)). *In the transition*, the process of releasing information generates more uncertainty by increasing the information asymmetry among dealers. On the other hand, it also reduces uncertainty by raising informational completeness and it increases both volume and volatility. The "switching point" is the *moment when information impounded into prices becomes higher than the noise created b the process of learning of the traders* i.e. the moment when the effects of higher informational completeness are exactly offset by those of higher informational asymmetry. At this point, the effect of active trade on volume and volatility becomes statistically insignificant. This point corresponds, on average, to the interval around 30 minutes after the originating trade. This time-varying pattern of the informational process is analogous across all the types of dealers.

Finally, the institutional classification does not seem to be relevant. Indeed, ordinary market makers and specialists do not significantly differ in terms of their impact when *they originate the trade* (active trade). They only differ in terms of the trade they intermediate (passive trade). That is, institutional differences do not affect the market impact of the strategies/reactions of the different dealers. On the contrary, it seems that trades with different informational content and/or market impact are directed to specific classes of dealers. In particular, the higher their informational content/impact, the more they tend to be placed with ordinary market makers as opposed to specialists. This fits with the fact that on average the predominant strategy in the market is hiding as opposed to experimenting and an ordinary market maker is a better dealer to trade with in the case a hiding strategy is pursued.

A corollary emerges from this analysis: *not all trade affects volume and volatility in the same way.* Quite the opposite: the class of traders which originates the greatest number of trades seems to impact the market less than the one which originates less, but more "salient" trade. This results reflects the fact that we are relaxing the anonymity assumption of the canonical model, as we discussed before.

Cross-sectionally, if we look at the weight of active trade versus other categories of trade, we see that, in the short run, active trade, by itself, has a limited impact on volatility, while it strongly affects volume. Its coefficient is half the size of that of passive trade for volatility, and approximately double the amount of that of passive trade for volume. These results fit with our intuition that, in the short run, active trade increases informational asymmetry. This raises volatility and boosts volume (Table 5). This is also consistent with the possibility that the strategy consists of hiding early and then exposing oneself once the desired position has been established. Indeed, if we consider the strategy-based classification, we see that the dealers who hide (i.e., sneakies) have a short-term impact muck lower that the dealers who experiment (i.e., skeptics). This holds both for the case of volume (coefficients for the first 10 minutes respectively equal to 0.726 and 1.144) and of volatility (coefficients for the first 10 minutes respectively equal to 1.12 and 41.97).

5.3.2. Daily horizon

The next question is to determine whether the aforesaid differential market impacts can aggregate at daily frequency. This would provide a link with the asset pricing literature and would be consistent with early results by, among others, Hasbrouck (1999) and Hasbrouck and Seppi (2001), that information effects on price from order flow are persistent and do not wash out at the end of the day. We therefore estimate:

$$\sigma_{k,t} = \alpha + \sum_{j=1}^{N} \beta_a^j \mathbf{X}_{a,k,t}^j + \delta \mathbf{C}_t + \varepsilon_{k,t} \tag{5.5}$$

where $\sigma_{k,t}$ is the daily volatility of the *k-th* bond and $X_{a,k,t}^j$ represents the sum of the total informed trades originated by dealers who belong to the *jth* category. The superscript j refers to the category considered within each classification (e.g., $j = \{scared$, $average$, $confident\}$ for the first classification). For each *k-th* bond we compute volatility and volume by aggregating individual transaction prices and trades respectively. $\mathbf{C}_t$ represents a vector of control variables. [33] WLS estimations are carried out.

[33] In particular, we consider two alternative specifications. In the first ones we use control variables to control for autocorrelation. The control variables are: the lag of the dependent variable (LAG(VOLAT.)) and the lag of the implied volatility of options on the futures on the BTP bonds (LAG(IV)). In the second specification, we correct the residuals assuming an autocorrelation structure up to the third lag.

The results (reported in Table 6) support our hypothesis. Trade affects volatility differently, depending on the class of traders who has originated it. Moreover, the differential impact is still statistically significant at the end of the day. In particular, the trade of the salient dealers impacts the market more than the originated by the other classes of traders. Furthermore, it is interesting to notice that there is a difference in the direction of the impact. That is, while scared, smart and sneaky dealers tend to increase volatility, confident, dumb and skeptic dealers tend to reduce it. At the daily level, if we consider the skeptics, we see that the process of experimentation, by disseminating information earlier, reduces volatility. On the contrary, adverse selection (i.e. trading by scared and smart investors) drives volatility up. This provides a direct evidence of the theoretical models describing it (Wang, 1993).

5.4. Reputation and forecastability

If trades generated by different classes of dealers have different impact on the market, the power of forecasts based on them should also differ. In particular, the fact that the salient dealers consistently have a stronger impact both in the short term and in the long term implies that their trade would be an ideal leading indicator of future market conditions. Their trades should have a higher out-of-sample forecasting power than the trade of the other classes of dealer as well as the overall aggregated trade. If we are capturing short-lived information, the forecasting power contained in the different types of trades should fade away relatively quickly.

In order to test this hypothesis, we use a VAR specification. This also helps us to overcome the fact that in the panel approach the explanatory variables are assumed exogenously predetermined.[34] A VAR structure does not have to pre-impose exogeneity

[34] A VAR also helps us to do away with the limitations caused by the fact that each single transaction is a separate event, without allowing for cross-correlation and/or causality among different trades.

on any variable, [35] and allows us to compare different specifications on a pure forecasting basis. We compare the forecasting power of different specifications at different lags and we test which one is the best in terms of Mean Square Forecasting Error (MSFE). In particular, we estimate a six-lag VAR [36]:

$$\mathbf{Y}^j_{k,t} = \mathbf{A} + \sum_{l=1}^{6} \mathbf{B}_l \mathbf{Y}^j_{i,t-l} + \mathbf{e}_t \tag{5.6}$$

where $\mathbf{Y}^j_{k.t} = [mv_{k,t}, \mathbf{X}^j_{k,t}]$. $mv_{k,t}$ represents, for the *k-th* bond, the market variable whose behavior we are interested in estimating (either volatility, or overall trading volume or return) and $\mathbf{X}^j_{k,t}$ is a vector that contains the stacked vectors of various types of trade of the different dealers. Analogously to before, the superscript j refers to the class of dealers whose behavior we are looking at. $\mathbf{A}$ and $\mathbf{B}_l$ are matrices of coefficients and $\mathbf{e}_t$ is a vector of residuals. We consider six 10-minutes lags (i.e. $l = 1, ..., 6$). In addition, the VAR contains dummies that allow for discontinuity in the data and morning/evening dummies. The discontinuity dummy takes value one if observations are not based on data from two consecutive ten minutes intervals, and zero otherwise. A similar dummy was used by Evans (1998). Morning and evening dummies take value one if the observation takes place in the intervals 9-10 a.m. and 4-5 p.m. and zero otherwise.[37] A separate VAR is estimated for each variable under consideration (return, volume and volatility) and for each class j under consideration.

We calculate the *t-th* period ahead forecasting errors for the *i-th* bond (i.e. $MSFE^j_{i,t} = \left[mv^j_{i,t} - \widehat{mv}^j_{i,t}\right]^2$), with $t = 10, 20, ..., 90$, for the *j-th* class-originated trade.[38] Then we

[35] Unless we specify *a priori* a causal ordering among the variables the same way, for instance, Evans (1998) does.

[36] Number of lags were chosen in accordance with Final Prediction Error criterion.

[37] We also performed robustness checks with dummies defined as one between 9:00 and 9:30 a.m. (morning) and 4:30 and 5:00 p.m. (evening) and zero otherwise. The results are very similar to the ones reported.

[38] We also consider for robustness a specification based on the innovations, by regressing the innovation

average the MSFEs across bonds for different time intervals and different bonds. That is:

$$MSFE_t^j = \sum_{i=1}^{N} \frac{MSFE_{i,t}^j}{N} \quad (5.7)$$

In Figure 1 we report the ratios between the $MSFE_t^j$ of the VARs estimated for the trade originated by the *j-th* class of dealers and the $MSFE_t$ of the VARs estimated using overall trading volume. *The lower the ratio, the higher the differential explanatory power* of the specific sub-component of total trade with respect to total trade.

The first thing to note is that active trade of the salient market markers is always a more powerful predictor than overall trading volume, at every time horizon. This holds for future returns, volume and volatility. This implies that the knowledge of a single component of active trade always provides a better forecast than the knowledge of overall trading volume.

Furthermore, the part of inter-dealer trading originated by market-makers only and excluding trade originated by ordinary dealers- is always more informative than overall trade. That is, the trade originated by ordinary dealers has a very low informational content. This fits with the institutional feature that ordinary dealers are always the smallest and least active traders in the market.

At a more disaggregated level, we see that trade generated by salient dealers (scared, smart and sneaky dealers) has always higher explanatory power than trade generated by least salient dealers (confident, dumb and skeptic dealers). This is consistent with the previous results. It is also interesting to note that for very long time intervals (70-90 minutes), the difference in forecasting power between classes of dealers blurs and disappears.

of bond returns on the innovations of the different components of trades.

6. Reputation and profitability

If this informationally motivated trade is speculative, we would expect dealers' profits to be directly related to the class they belong to. In particular, if adverse selection affects dealers' behavior, we would expect that the dealers that mostly suffer out of it ("scared") should be the ones who are willing to sacrifice part of their profits to reduce adverse selection. This implies that the profits of the scared should be lower than the profits of the confident. On the other end, we would expect smart investors to make more profits than the dumb ones. Finally, if we consider dealers' strategies, we would expect that dealers who experiment pay a price for their experimentation. This implies that skeptics' profits should be lower than that of sneakies.

To test these hypotheses, we construct dealers' profits. Profits are defined as total profit (both from active and passive trade) of a trade within 10 minutes after the originating transaction. They are constructed as the difference between the price at which the bond was bought (sold) and the closing price of the day. Transactions in thinly traded bonds (less than 25 transaction per day), and transactions within 10 minutes of the closing price have been excluded. Profits broken down by class of dealers are reported in Table 7. In particular, we report the descriptive statistics of the profits disaggregated by the type of dealer originating the trade (Panel A) and statistical tests of the difference between the profits of different classes of dealers (Panel B).[39]

The results are consistent with our intuition. First, dealers belonging to different classes display statistically different profits for all the trade-based classifications. In particular, the *p-value* of the difference is always lower than 0.001 when we consider the opposite classes (i.e., confident/scared, sneaky/skeptic, smart/dumb). However, the institutional classification does not provide statistically significant results even with a

[39] Given that the distribution of profits displays high skewness and kurtosis, we focus on the tests of the differences of the median (*Wilcoxon two-sample test*).

5% confidence level. This is consistent with the fact that the institutional classification hardly captures significant differences in dealers' behavior.

If we then consider the classes based on trade-based classifications, we see that the results confirm our hypotheses. Indeed, experimentation is costly as the skeptics display lower profits than the sneakies who immediately reap the benefit of their informational advantage. That is, skeptics dealers display consistently lower profits than the sneakies.

Adverse selection induces the scared dealers to enact trades which provide them with consistently lower profits than the ones of the confident investors. Finally, the smart investors make more profits. This is expected and it is due to the structure of the market. Indeed, while everybody agrees that a smart investor may have privileged information/higher ability, no market maker can directly discriminate against him. Indeed, each market maker has to post bid and ask quotes at which to trade that are available to all the dealers in the market and he gets to know the identity of the dealer placing the incoming order only after the order has been posted. This allows the smart dealers to make profits, even if (presumably) at the expense of higher cost for all the dealers overall.

In order to assess the robustness of our results, we re-estimated profits by following the methodology developed by Hasbrouck and Sofianos (1993). We therefore used spectral decomposition to define short term, medium term and log term profits. The spectrum is divided into short-term (less than 10 transactions), medium-term, and long term (more than 100 transactions). The results (not reported [40]) are consistent with the reported ones. In particular, it is interesting to note that experimentation delivers higher profits and that most of the profits are long-term ones. Both strategies, "sneaking" and experimentation are costly in the short run and deliver short-term losses. Also, as expected, smart dealers generate higher profits than the dumb ones. Again, most of these profits are long-term ones.

[40] They are available upon request from the authors.

Finally, we can try to directly link the strategies played by the different classes of dealers to their own corporate characteristics. In this case, 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 implies higher informational advantage and stronger incentive to hide. The skeptics, instead, are medium-sized highly efficient banks. The relatively small size would justify high risk aversion or, in any case, higher cautiousness.[41]

7. Conclusions

We studied the impact of reputation on dealers' behavior. We identified different classes of dealers defined in terms of their perception of the ability of the other dealers surrounding them as well as in terms of the perception that the overall market has about their ability. We also grouped them in terms of the way they strategically react to the informational content of the incoming trade on the basis of the reputation of the dealers placing it. Among these dealers, we identified the "salient" ones, that is the dealers whose trades have the strongest market impact.

We showed that in the very short run, the market is less deep when the trade has been originated by a salient dealer and that the trade originated by salient dealers has a stronger impact over time. Moreover, we showed that the differential impact is still statistically significant at the end of the day and that the daily trade of the salient dealers impacts the market more than the one originated by the other classes of traders. Differences in impact seem to correspond to differences in profitability, that is dealers belonging to different classes display statistically different profits.

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

We used the fact that salient dealers consistently have a stronger impact both in the short term and in the long term, to construct leading indicators of future market conditions. In particular, we showed that the trades of the salient dealers have a higher out-of-sample power to forecast future returns, volume and volatility than the trade of the other classes of dealer as well as the overall aggregated trade, at every time horizon.

These results provide many implications for future theoretical research. One possibility is the formal relaxation of the assumption of market anonymity, so as to make the determination of prices for the market maker and the reaction of the dealers dependent on the identity of the dealer placing the incoming order. Moreover, it would be interesting to directly analyze the implications of allowing the market maker to optimally choose between changing the bid-ask spread and directly placing orders with other dealers.

Also, our analysis has been restricted to the trade in the secondary market. We can conjecture that dealers may coordinate their behavior in both the primary and the secondary market when there is an auction. This would involve an analysis of the joint trade in the two markets as well as an investigation of how the standard models of bidding behavior at the auction have to be changed once the reputation developed in the secondary market is accounted for.

These results also may help to shed some light on the interaction between the type of market structure and its institutional features. Indeed, reputation and dealers strategic interaction depend on the amount of information existing in the market and therefore on the degree of transparency dealers deal with. It would be also interesting to consider how regulation should tackle the issue of endogenous development of reputation among market participants. In particular, it is possible that some types of regulations and disclosure rules may prevent the development of reputation or may make it very short-term. If reputation favors a quick impounding of information in prices, this enforced transparency may paradoxically hamper market efficiency.

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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 28th, 1994 to February 28, 1996. Panel A describes the bonds. Panel B reports statistics of daily volume per intermediating market maker. Panel C breaks down trade by different trade sizes. All volume variables are expressed as face value.

Panel A: Types of Bonds

		Daily Volume Statistics (Bln. Lire)	
Bond Type	Transactions	Mean	Std. Dev.
Medium and Long-Term T-Bond (BTP)	1,081,945	17,990	5,100
Financially Indexed Bonds (CCT)	301,306	5,590	4,500
Zero-coupon T-Notes (CTZ)	10,186	190	120

Panel B: Daily Volume Statistics per dealer (bln. Lire)

Market Maker Type	Daily Median # of dealers	Mean	Std. Dev.	Max
Overall	42	413.08	355.75	4175.00
Official Classification				
Specialist	15	658.85	384.46	4175.00
Ordinary Market Maker	27	283.57	258.50	2550.00
Reaction-based Classification 1				
Confident	17	455.79	424.89	4,675.00
Average	13	650.94	426.19	2,955.00
Scared	12	718.62	388.14	3,035.00
Reaction-based Classification 2				
Dumb	17	520.79	421.46	3,100.00
Average	12	634.70	445.25	4,675.00
Smart	13	637.11	409.96	3,665.00
Strategy-based Classification				
Sneaky	9	679.11	461.55	4675.00
Average	29	551.91	404.93	3100.00
Skeptic	4	637.70	505.18	3035.00

Panel C: Size distribution of transactions

Transaction size (bln Lire)	5	10	15	20	>20
Fraction of overall transactions	88.1%	10.1%	1.0%	0.4%	0.4%

Table 2: Market makers' prior over other dealers' informativeness

We report the statistics of the learning coefficient γ_{ji} in the regression $\Delta P_{k,t+5} = \gamma_{ji} T_{jik,t} + \varepsilon_{jik,t+1}$. For each trading day we consider the pairwise relation of each dealer *j* versus all the other *i* dealers in previous ten days. $\Delta P_{k,t+5} = P_{k,t+5} - P_{k,t}$ is the change in price $P_{k,t}$ in the 5 minutes following the originating transaction. We define $T_{jik,t}$ as the signed volume of trade received by the *jth* market maker from the *ith* dealer in *k-th* bond at time *t*. For each single market maker a vector is defined that contains his estimates of the degree of informativeness of all the other dealers, (γ_{ji}). In Panel A we report the statistics for γ_{ji} along with the result of *t-test* of the hypothesis $\gamma_{ji}=0$. We report the statistics for all the γ_{ji}'s (calculated if the number of observations in the regression M>4) and for all the statistically significant γ_{ji}'s separately. In addition, we report the γ_{ji}'s averaged over intermediating and originating dealer. The reported γ_{ji}'s were multiplied by 1000. Panel B reports the transitional probability of having γ_{ji} statistically significant conditional on statistical significance of γ_{ji} 10 trading days before. Panel C reports the probabilities of being classified as market maker of type i conditional on the probability to be classified as market maker of type j 10rading days before. The time dependence of those probabilities is shown in Figure 1.

Panel A: Learning coefficient γ

Intermediating Dealer	Originating Dealer	N	Mean	Std. Dev.	Max.	Min.	t-stat.
Overall (all significant)		57,634	1.30	2.52	21.42	-23.47	123.6
Overall (all with M>4)		486,002	0.39	1.54	24.62	-31.90	177.5
Specialist	Specialist	9,611	1.31	1.37	8.91	-8.76	94.1
Specialist	Ord. Market Maker	12,661	1.27	2.29	12.23	-12.82	62.3
Specialist	Ord. Dealer	4,027	0.47	3.66	18.65	-19.90	8.12
Ord. Market Maker	Specialist	13,062	1.57	2.15	13.55	-10.73	83.3
Ord. Market Maker	Ord. Market Maker	14,091	1.51	2.66	12.27	-15.65	67.5
Ord. Market Maker	Ord. Dealer	4,182	0.62	3.87	21.42	-23.47	10.3

Panel B: Deterioration of reputation

		At t+10 trading days				
		$p>0.9, \gamma<0$	$0.5<p\leq0.9, \gamma<0$	$P\leq0.5, \gamma<0$	$0.5<p\leq0.9, \gamma>0$	$p>0.9, \gamma>0$
At t	$p>0.9, \gamma<0$	0.177	0.259	0.463	0.082	0.019
	$0.5<p\leq0.9, \gamma<0$	0.137	0.249	0.498	0.093	0.022
	$p\leq0.5, \gamma<0$	0.056	0.110	0.762	0.056	0.015
	$0.5<p\leq0.9, \gamma>0$	0.096	0.206	0.550	0.113	0.034
	$p>0.9, \gamma>0$	0.083	0.171	0.567	0.131	0.049

Panel C: Transitional probability matrix for different classification of the dealers

Classification at t	Classification at t+10 trading days		
	Confident	Average	Scared
Confident	0.728	0.173	0.097
Average	0.341	0.339	0.314
Scared	0.196	0.313	0.489
	Dumb	Average	Smart
Dumb	0.711	0.172	0.115
Average	0.336	0.338	0.324
Smart	0.241	0.314	0.443

Table 3: Volatility after the transaction

This table reports the statistics of price volatility in the interval [t,t+10min] and [t+10min, t+20min] (σ_{10} and σ_{20} correspondingly) after the transaction that was intermediated by a particular class of dealer. We report the results for three different classifications. In all of them only *informed* transactions were selected (i.e., transactions where γ has *p-value* greater than 90%). The results of *t-test* of the hypothesis that the means of the two groups are equal are presented. Price volatility is multiplied by 10,000. Panel D reports the result of WLS estimate of the regression $\sigma_j=\alpha_0+\alpha_H H_{it}+\beta C$, where H_{it} is given either by Eq. (2) for classification 1or by Eq. (3) for classification 2. C represents lagged control variables (volatility over past 10 minutes, σ_{-10M}, and 1 hour, σ_{-1H}). T-statistics is reported in parenthesis. Estimates are multiplied by 10,000.

					T-test			
Variable	Intermediary	**N**	Mean	Std. Dev.	*t-stat*	*p-value*	*t-stat*	*p-value*
				Panel A: Reaction-based Classification 1				
					Average		Scared	
σ_{10}	Confident	56,218	5.42	14.46	-5.20	<.0001	-14.55	<.0001
	Average	78,522	5.86	15.50			-9.91	<.0001
	Scared	111,493	6.63	17.02				
σ_{20}	Confident	56,218	4.94	12.63	-3.74	0.0002	-10.71	<.0001
	Average	78,522	5.30	14.98			-7.00	<.0001
	Scared	111,493	5.94	16.70				
				Panel B: Reaction-based Classification 2				
					Average		Smart	
σ_{10}	Dumb	62,386	4.95	14.15	-12.52	<.0001	-2.35	0.0187
	Average	77,144	6.09	15.92			-11.14	<.0001
	Smart	106,703	6.28	16.15				
σ_{20}	Dumb	62,386	4.50	14.20	-9.09	<.0001	-1.67	0.0945
	Average	77,144	5.50	15.38			-10.62	<.0001
	Smart	106,703	5.66	15.49				
				Panel C: Strategy-based Classification				
					Average		Skeptic	
σ_{10}	Sneaky	53,599	6.14	16.36	2.79	0.0053	-8.47	<.0001
	Average	162,735	5.91	15.52			12.57	<.0001
	Skeptic	29,899	7.23	18.03				
σ_{20}	Sneaky	53,599	5.56	16.58	2.51	0.0122	-6.13	<.0001
	Average	162,735	5.33	14.46			10.02	<.0001
	Skeptic	29,899	6.51	17.73				

Panel D: Linear regression of volatility

	Dependent Variable											
			σ_{10}							σ_{20}		
Variable	**Value**	***t-stat.***	**Value**	***t-stat.***	**Value**	***t-stat.***	**Value**	***t-stat.***	**Value**	***t-stat.***	**Value**	***t-stat.***
						Reaction-based classification 1						
INTERCEPT	2.86	(21.05)	2.06	(22.93)	2.07	(20.72)	1.84	(22.94)	1.33	(20.94)	1.33	(20.78)
α_h	132.75	(16.39)	95.09	(16.08)	95.19	(15.09)	89.41	(16.58)	65.23	(13.94)	65.25	(13.82)
σ_{-10M}	0.22	(7.01)			0.08	(2.67)	0.10	(6.74)			0.01	(0.97)
σ_{-1H}			0.12	(25.79)	0.10	(17.19)			0.07	(24.20)	0.06	(19.74)
Adjusted R^2	0.0661		0.0933		0.0985		0.0236		0.0442		0.0444	
						Reaction-based classification 2						
INTERCEPT	2.03	(16.23)	1.47	(15.37)	1.48	(14.85)	1.32	(16.79)	0.96	(14.18)	0.96	(14.15)
α_k	81.07	(17.25)	57.96	(16.86)	58.10	(15.63)	53.38	(19.24)	38.56	(17.02)	38.59	(16.81)
σ_{-10M}	0.22	(7.01)			0.08	(2.68)	0.10	(6.74)			0.01	(0.98)
σ_{-1H}			0.12	(25.71)	0.10	(17.12)			0.07	(24.20)	0.06	(19.79)
Adjusted R^2	0.0664		0.0935		0.0987		0.0237		0.0442		0.0444	

Table 4: Market Depth and type of market makers

This table reports estimates of market depth. λ_{GH} is the estimate of market depth from Glosten and Harris specification, $\Delta p_{i,t} = \lambda_i q_{i,t} + \psi(D_{i,t} - D_{i,t-1}) + \varepsilon_{i,t}$; λ_{MS} is the estimate of market depth from Madhavan and Smidt specification: $\Delta p_{i,t} = \lambda_i q_{i,t} + (\psi/\pi)D_{i,t} - \psi D_{i,t-1} + (\gamma/\pi)I_{i,t} - \gamma I_{i,t-1} + \eta_{i,t}$. Here $\Delta p_{i,t}$ is the price change at transaction originated by a dealer belonging to the *ith* class at time *t*, and $q_{i,t}$ is the signed order flow at time *t* of the trade originated by such a dealer, $D_{i,t}$ denotes the sign of the order placed by the dealer belonging to the *i-th* class at time *t* (+1 for a buyer-initiated trade and -1 for a seller-initiated trade), $D_{i,t-1}$ is the sign of the order immediately preceding the order placed by the dealer belonging to the *ith* class at time *t*, and $\pi=1/(1+\alpha\lambda)$. DUMMY takes the value 1 if transaction is originated by ordinary market maker and 0 otherwise. I_t represents market maker's inventory at time *t*. There is no serial correlation for ε_t, in the Glosten-Harris specification, while we use a MA(1) for η_t in the Madhavan-Smidt specification. The subscript *i* refers to the category considered within each classification. Both specifications are estimated by pooling all the observations and using dummies to differentiate on the basis of the dealers originating them. We also report the result of Wald tests of the difference between λ's for different classes of dealers. 246,233 observations are used. Estimates of γ are multiplied by 1,000,000. All other estimates, except α, are multiplied by 1,000.

	Glosten-Harris Specification		Madhavan-Smidt Specification	
Panel A: Reaction-based Classification 1				
Variable	Value	*t-stat.*	Value	*t-stat.*
$\lambda_{CONFIDENT}$	0.319	(39.91)	0.797	(122.72)
$\lambda_{CONFIDENT}$ x $DUMMY_{OMM}$	0.072	(16.38)	0.093	(21.08)
$\lambda_{AVERAGE}$	0.487	(63.88)	0.980	(162.09)
$\lambda_{AVERAGE}$ x $DUMMY_{OMM}$	0.040	(3.54)	0.044	(5.47)
λ_{SCARED}	0.632	(90.09)	1.088	(192.19)
λ_{SCARED} x $DUMMY_{OMM}$	-0.020	(-1.75)	0.005	(0.66)
ψ	-5.380	(-235.94)	-2.480	(-112.65)
α	-	-	1180.480	(130.47)
γ	-	-	0.482	(8.14)
Adjusted R^2	0.088		0.068	
Hypothesis	χ^2	p-value	χ^2	p-value
$\lambda_{CONFIDENT}=\lambda_{AVERAGE}=\lambda_{SCARED}$	994.8	<.0001	1625.6	<.0001
$\lambda_{CONFIDENT}=\lambda_{AVERAGE}$	250.3	<.0001	538.8	<.0001
$\lambda_{CONFIDENT}=\lambda_{SCARED}$	969.0	<.0001	1560.3	<.0001
$\lambda_{AVERAGE}=\lambda_{SCARED}$	229.6	<.0001	283.2	<.0001
Panel B: Reaction-based Classification 2				
Variable	Value	*t-stat.*	Value	*t-stat.*
λ_{DUMB}	0.457	(63.26)	0.964	(179.45)
λ_{DUMB} x $DUMMY_{OMM}$	0.051	(9.34)	0.037	(11.94)
$\lambda_{AVERAGE}$	0.536	(70.62)	1.027	(183.79)
$\lambda_{AVERAGE}$ x $DUMMY_{OMM}$	-0.030	(-3.03)	-0.020	(-3.02)
λ_{SMART}	0.526	(69.94)	1.027	(186.13)
λ_{SMART} x $DUMMY_{OMM}$	0.009	(0.75)	-0.010	(-1.51)
ψ	-5.350	(-234.07)	-3.050	(-131.12)
α	-	-	1210.180	(149.48)
γ	-	-	0.212	(20.91)
Adjusted R^2	0.088		0.072	
Hypothesis	χ^2	p-value	χ^2	p-value
$\lambda_{DUMB}=\lambda_{AVERAGE}=\lambda_{SMART}$	108.58	<.0001	170.21	<.0001
$\lambda_{DUMB}=\lambda_{AVERAGE}$	77.13	<.0001	115.81	<.0001
$\lambda_{DUMB}=\lambda_{SMART}$	47.17	<.0001	103.02	<.0001
$\lambda_{AVERAGE}=\lambda_{SMART}$	8.24	0.0163	1.68	0.4326
Panel C: Strategy-based classification				
Variable	Value	*t-stat.*	Value	*t-stat.*
λ_{SNEAKY}	0.380	(42.97)	0.940	(147.69)
λ_{SNEAKY} x $DUMMY_{OMM}$	0.151	(12.49)	0.042	(5.10)
$\lambda_{AVERAGE}$	0.914	(63.43)	1.236	(126.21)
$\lambda_{AVERAGE}$ x $DUMMY_{OMM}$	-0.430	(-17.90)	-0.220	(-14.63)
$\lambda_{SKEPTIC}$	0.495	(93.09)	0.997	(227.78)
$\lambda_{SKEPTIC}$ x $DUMMY_{OMM}$	0.046	(6.04)	0.055	(10.67)
ψ	-5.360	(-234.76)	-2.970	(-129.00)
α	-	-	1195.890	(147.74)
γ	-	-	0.142	(18.80)
Adjusted R^2	0.089		0.072	
Hypothesis	χ^2	p-value	χ^2	p-value
$\lambda_{SNEAKY}=\lambda_{SKEPTIC}=\lambda_{AVERAGE}$	1057.0	<.0001	877.9	<.0001
$\lambda_{SNEAKY}=\lambda_{SKEPTIC}$	1019.1	<.0001	738.7	<.0001
$\lambda_{SNEAKY}=\lambda_{AVERAGE}$	131.9	<.0001	167.8	<.0001
$\lambda_{SKEPTIC}=\lambda_{AVERAGE}$	765.8	<.0001	603.8	<.0001

Table 5. Differential impact of active and passive trade on volume and volatility

This table reports the results of the tests of active and passive trade on both volume and volatility disaggregated on the basis of the type of intermediating dealer (Reaction-based classification 1 is reported in Panel A, reaction-based classification 2 is reported in panel B and the strategy-based classification is reported in panel C). We estimate:

$$mv_{[t+T,t+T+10]}=\text{INT} + \Sigma_i(\text{ACT}_{,i}\, X_{\text{ACT},i,[t,t+10]} + \text{PASS}_i\, X_{PASS,i,[t,t+10]})d_i + \text{MORNING}\ D_{\text{MORN}} + \text{EVENING}\ D_{\text{EVE}} + \text{CTRL1}\ mv_{[t-60,t]} + \text{CTRL2}\ mv_{[t-10,t]}+\text{INVENTORY}^*\ I^k_{t,i} +\varepsilon_{it}$$

where $mv_{[t+T,t+T+10]}$ represents either return, overall trading volume or volatility in the time interval [t,t+T] for a particular bond transacted at time t. t is defined as transaction time, while T represents the end of the interval we consider. In particular, T = 0,10,20,30,40,50 minutes. X_{ACT} and X_{PAS} are, respectively, the active and passive trade in which market maker, who intermediates the transaction at time *t*, is involved within 10 minutes following the intermediating transaction. d_i is the dummy variable that takes value 1 if market maker belongs to type *i*, and 0 otherwise. D_{MORN} and D_{EVE} are dummy variables that take value 1 if the transaction initiated between 9AM-10AM and 4PM-5PM correspondingly, and zero otherwise. The lagged dependent variable (1 hours and 10 minutes before the transaction) $mv_{[t-60,t]}$ and $mv_{[t-10,t]}$ is used to control for momentum effects. I^k_t represents inventory of intermediating dealer in bond k at transaction time t, $I_t=\Sigma^{t-1}_{s=-\infty}Q_t$., Q are previous market makers' buys/sells (including auction allocations). Estimations are done using a weighted least-square estimator with correction for heteroscedasticity. The *t-statistics* are reported in parentheses. We also report the results of Wald test of the restrictions of the coefficients in the model. 246,233 observations were used. The estimated values of $\text{ACT}_{,I}$, $\text{PASS}_{,i}$, MORNING and EVENING are multiplied on 10,000,000.

Panel A: Reaction-based classification 1

	Value	t-stat.	Value	t-stat.	Value	t-stat.	Value	t-stat.	Value	t-stat.	Value	t-stat.
Volume												
PAS	0.354	(4.49)	0.410	(4.44)	0.232	(4.19)	-0.122	(-4.70)	-0.138	(-5.53)	0.037	(1.99)
ACT	0.722	(12.34)	0.692	(11.01)	0.392	(10.77)	-0.209	(-10.86)	-0.183	(-10.36)	0.142	(8.72)
PAS	0.414	(7.11)	0.504	(7.84)	0.286	(7.18)	-0.187	(-8.47)	-0.157	(-7.85)	0.086	(5.50)
ACT	1.031	(13.70)	1.185	(13.13)	0.697	(13.31)	-0.284	(-10.95)	-0.276	(-11.69)	0.231	(9.94)
PAS	0.650	(17.57)	0.764	(15.76)	0.444	(14.97)	-0.209	(-13.73)	-0.194	(-12.91)	0.120	(7.66)
ACT	1.177	(43.25)	1.405	(42.88)	0.799	(36.43)	-0.402	(-36.13)	-0.389	(-34.27)	0.276	(22.32)
MORNING	70.547	(149.28)	60.884	(116.05)	45.845	(123.18)	39.824	(101.68)	45.980	(111.93)	62.731	(152.03)
EVENING	-2.825	(-13.42)	1.956	(8.54)	-2.421	(-13.67)	-20.829	(-123.44)	-36.738	(-184.78)	-50.471	(-239.66)
VOLUM_1H	0.122	(136.59)	0.115	(115.19)	0.121	(170.86)	0.052	(85.00)	-0.006	(-9.23)	0.011	(18.79)
VOLUM_10M	0.201	(85.71)	-0.103	(-42.08)	-0.290	(-156.63)	0.130	(63.71)	0.499	(206.65)	0.518	(231.17)
INVENTORY	-0.008	(-30.95)	-0.009	(-29.84)	-0.005	(-25.46)	-0.001	(-4.25)	-0.002	(-8.80)	-0.005	(-18.37)
Adjusted R^2	0.499		0.280		0.231		0.192		0.376		0.463	
HYPOTHESIS	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**
∀												
PAS = PAS	0.37	0.5414	0.71	0.3993	0.64	0.4245	3.69	0.0546	0.38	0.5384	4.06	0.0438
PAS = PAS	11.82	0.0006	11.93	0.0006	11.75	0.0006	8.51	0.0035	3.82	0.0507	11.88	0.0006
PAS = PAS	11.68	0.0006	10.39	0.0013	10.09	0.0015	0.64	0.4247	2.13	0.1448	2.37	0.1238
ACT = ACT	11.66	0.0006	22.25	<.0001	25.24	<.0001	6.01	0.0142	11.03	0.0009	10.74	0.001
ACT = ACT	57.91	<.0001	115.78	<.0001	103.92	<.0001	86.76	<.0001	108.45	<.0001	47.51	<.0001
ACT = ACT	4.10	0.0429	6.34	0.0118	3.87	0.0491	20.57	<.0001	21.39	<.0001	3.32	0.0683
Volatility												
PAS	-4.72	(-4.93)	0.04	(0.04)	-0.06	(-0.10)	-3.89	(-4.47)	-5.24	(-4.45)	-5.38	(-5.26)
ACT	3.29	(4.63)	9.88	(10.93)	6.41	(11.15)	-4.81	(-9.03)	-6.86	(-9.40)	-2.46	(-4.18)
PAS	-0.16	(-0.12)	3.90	(2.66)	4.69	(3.67)	-6.24	(-8.48)	-7.56	(-8.02)	-5.40	(-6.56)
ACT	9.14	(7.12)	21.64	(10.90)	12.09	(9.67)	-7.36	(-9.53)	-9.15	(-9.61)	-0.22	(-0.32)
PAS	3.01	(1.81)	9.62	(5.84)	5.92	(5.70)	-6.70	(-10.40)	-9.17	(-12.13)	-6.27	(-7.25)
ACT	28.71	(16.38)	38.34	(24.79)	22.53	(21.68)	-9.22	(-16.48)	-10.80	(-15.87)	5.76	(6.49)
MORNING	3150.00	(10.88)	820.00	(7.17)	-200.00	(-5.62)	760.00	(10.42)	1310.00	(10.75)	830.00	(5.46)
EVENING	1740.00	(20.01)	2040.00	(39.63)	1370.00	(35.39)	-85.10	(-2.85)	-400.00	(-9.61)	-200.00	(-4.31)
VOLAT_1H	0.08	(4.47)	0.05	(4.49)	0.04	(4.53)	0.03	(4.49)	0.04	(4.44)	0.05	(4.45)
VOLAT_10M	0.01	(0.29)	-0.01	(-0.67)	-0.03	(-2.50)	-0.01	(-0.63)	0.00	(0.11)	0.00	(0.05)
INVENTORY	-0.81	(-9.28)	-0.72	(-13.66)	-0.37	(-9.39)	-0.30	(-9.11)	-0.53	(-12.87)	-0.83	(-15.68)
Adjusted R^2	0.066		0.041		0.031		0.036		0.040		0.039	
HYPOTHESIS	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**
∀												
PAS = PAS	11.57	0.0007	5.12	0.0237	11.95	0.0005	4.58	0.0323	2.56	0.1096	0.00	0.9905
PAS = PAS	21.27	<.0001	26.57	<.0001	27.12	<.0001	7.40	0.0065	8.78	0.003	0.52	0.4694
PAS = PAS	3.06	0.0801	7.09	0.0077	0.58	0.4444	0.25	0.6152	2.14	0.1432	0.73	0.3926
ACT = ACT	16.59	<.0001	31.05	<.0001	17.77	<.0001	7.73	0.0054	3.88	0.049	6.01	0.0142
ACT = ACT	164.22	<.0001	257.29	<.0001	184.89	<.0001	31.59	<.0001	15.05	0.0001	53.13	<.0001
ACT = ACT	97.68	<.0001	51.14	<.0001	48.11	<.0001	4.77	0.0289	2.36	0.1242	35.00	<.0001

Panel B: Reaction-based classification 2

	0-10min		10-20min		20-30min		30-40min		40-50min		50-60min	
	Value	t-stat	Value	t-stat	Value	t-stat	Value	t-stat	Value	t-stat	Value	t-stat
Volume												
INTERCEPT	27.192	(81.58)	17.206	(46.62)	12.278	(51.97)	10.379	(46.38)	19.173	(79.84)	28.386	(110.11)
PAS_{DUMB}	0.454	(9.46)	0.448	(8.14)	0.284	(7.21)	-0.118	(-7.83)	-0.119	(-6.32)	0.054	(3.04)
ACT_{DUMB}	0.923	(23.31)	1.021	(21.06)	0.581	(20.41)	-0.306	(-21.05)	-0.274	(-19.54)	0.091	(13.34)
$PAS_{AVERAGE}$	0.274	(3.35)	0.366	(3.51)	0.188	(3.16)	-0.121	(-4.04)	-0.121	(-4.65)	0.062	(2.76)
$ACT_{AVERAGE}$	0.867	(11.81)	0.896	(10.69)	0.527	(10.93)	-0.232	(-9.63)	-0.227	(-10.14)	0.156	(8.06)
PAS_{SMART}	0.654	(15.93)	0.818	(14.91)	0.457	(14.32)	-0.278	(-13.34)	-0.253	(-14.24)	0.086	(5.75)
ACT_{SMART}	1.034	(25.43)	1.217	(25.92)	0.683	(23.35)	-0.336	(-22.19)	-0.314	(-21.38)	0.251	(17.68)
MORNING	71.526	(148.02)	62.297	(115.87)	46.709	(123.42)	39.515	(100.63)	45.648	(111.10)	63.054	(152.76)
EVENING	-2.923	(-13.91)	1.765	(7.74)	-2.521	(-14.27)	-20.770	(-123.41)	-36.684	(-184.86)	-50.506	(-239.93)
VOLUM_1H	0.123	(138.51)	0.117	(117.05)	0.122	(173.01)	0.052	(84.72)	-0.006	(-9.73)	0.012	(19.37)
VOLUM_10M	0.200	(85.45)	-0.104	(-42.55)	-0.290	(-156.76)	0.130	(63.85)	0.499	(206.77)	0.517	(231.09)
INVENTORY	-0.007	(-25.14)	-0.008	(-23.97)	-0.005	(-21.07)	-0.001	(-5.82)	-0.002	(-10.10)	-0.004	(-17.42)
Adjusted R^2	0.496		0.273		0.226		0.192		0.375		0.463	
HYPOTHESIS	**Wald**	**p**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**
$PAS_i = ACT_j, \forall i,j$	87.32	<.0001	71.41	<.0001	55.80	<.0001	62.75	<.0001	39.89	<.0001	80.33	<.0001
$PAS_{DUMB} = PAS_{AVERAGE}$	3.64	0.0565	0.49	0.485	1.84	0.1751	0.01	0.9093	0.00	0.9459	0.09	0.7593
$PAS_{DUMB} = PAS_{SMART}$	10.24	0.0014	23.05	<.0001	11.96	0.0005	39.48	<.0001	27.27	<.0001	2.02	0.1555
$PAS_{SMART} = PAS_{AVERAGE}$	17.73	<.0001	15.18	<.0001	16.55	<.0001	18.94	<.0001	18.03	<.0001	0.80	0.3697
$ACT_{DUMB} = ACT_{AVERAGE}$	0.52	0.4695	1.90	0.1684	1.09	0.2975	7.99	0.0047	3.59	0.0581	7.30	0.0069
$ACT_{DUMB} = ACT_{SMART}$	4.57	0.0325	9.97	0.0016	7.15	0.0075	2.37	0.1239	4.47	0.0345	11.19	0.0008
$ACT_{SMART} = ACT_{AVERAGE}$	4.61	0.0319	12.75	0.0004	8.79	0.0030	15.26	<.0001	12.09	0.0005	17.48	<.0001
Volatility												
INTERCEPT	0.0003	(9.57)	0.0002	(9.10)	0.0001	(6.74)	0.0001	(12.29)	0.0002	(16.44)	0.0003	(17.76)
PAS_{DUMB}	-13.60	(-7.95)	-9.23	(-7.46)	-4.58	(-4.22)	-4.81	(-6.18)	-7.60	(-7.25)	-0.18	(-0.32)
ACT_{DUMB}	11.10	(8.81)	17.32	(10.57)	10.04	(10.14)	-5.32	(-8.42)	-6.73	(-8.48)	0.36	(0.45)
$PAS_{AVERAGE}$	-3.01	(-2.79)	0.54	(0.38)	1.31	(1.32)	-3.51	(-3.84)	-4.59	(-3.91)	0.05	(0.08)
$ACT_{AVERAGE}$	12.15	(11.20)	23.79	(19.16)	14.25	(16.07)	-8.28	(-16.35)	-10.30	(-15.71)	-4.08	(-4.92)
PAS_{SMART}	15.04	(9.60)	23.72	(11.29)	13.98	(11.65)	-8.06	(-12.31)	-8.75	(-11.69)	2.35	(3.55)
ACT_{SMART}	15.93	(11.31)	24.39	(16.36)	14.48	(15.28)	-7.14	(-15.53)	-9.26	(-16.53)	-11.60	(-9.99)
MORNING	3180.00	(10.96)	850.00	(7.41)	-200.00	(-5.16)	750.00	(10.33)	1310.00	(10.68)	840.00	(5.48)
EVENING	1730.00	(19.98)	2030.00	(39.55)	1370.00	(35.32)	-83.70	(-2.82)	-400.00	(-9.63)	-200.00	(-4.39)
VOLAT_1H	0.08	(4.47)	0.05	(4.50)	0.04	(4.53)	0.03	(4.49)	0.04	(4.44)	0.05	(4.45)
VOLAT_10M	0.01	(0.29)	-0.01	(-0.67)	-0.03	(-2.50)	-0.01	(-0.63)	0.00	(0.11)	0.00	(0.05)
INVENTORY	-0.78	(-9.02)	-0.69	(-13.07)	-0.35	(-8.93)	-0.31	(-9.51)	-0.54	(-13.30)	-0.83	(-15.77)
Adjusted R^2	0.065		0.041		0.031		0.036		0.039		0.039	
HYPOTHESIS	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**
$PAS_i = ACT_j, \forall i,j$	126.14	<.0001	238.94	<.0001	122.91	<.0001	11.14	0.0110	4.64	0.2004	55.91	<.0001
$PAS_{DUMB} = PAS_{AVERAGE}$	43.78	<.0001	29.92	<.0001	17.40	<.0001	1.31	0.2527	4.16	0.0414	0.08	0.7729
$PAS_{DUMB} = PAS_{SMART}$	145.31	<.0001	177.18	<.0001	125.92	<.0001	9.78	0.0018	0.79	0.3755	9.27	0.0023
$PAS_{SMART} = PAS_{AVERAGE}$	90.08	<.0001	83.38	<.0001	66.18	<.0001	16.63	<.0001	9.12	0.0025	7.40	0.0065
$ACT_{DUMB} = ACT_{AVERAGE}$	0.47	0.4934	11.26	0.0008	11.29	0.0008	15.33	<.0001	13.90	0.0002	14.50	0.0001
$ACT_{DUMB} = ACT_{SMART}$	4.38	0.0363	11.27	0.0008	11.58	0.0007	6.01	0.0142	7.55	0.0060	67.20	<.0001
$ACT_{SMART} = ACT_{AVERAGE}$	2.58	0.1082	0.11	0.7410	0.03	0.8516	3.30	0.0694	1.83	0.1767	36.55	<.0001

Panel C: Strategy-based classification

	0-10min		10-20min		20-30min		30-40min		40-50min		50-60min	
	Value	t-stat	Value	t-stat	Value	t-stat	Value	t-stat	Value	t-stat	Value	t-stat
Volume												
INTERCEPT	26.627	(80.08)	16.527	(43.53)	11.832	(48.74)	10.539	(48.29)	19.319	(81.79)	28.206	(113.18)
PAS_{SNEAKY}	0.378	(4.20)	0.456	(4.14)	0.270	(4.08)	-0.167	(-4.78)	-0.161	(-5.42)	0.065	(2.94)
ACT_{SNEAKY}	0.726	(11.53)	0.728	(10.37)	0.407	(10.11)	-0.179	(-8.40)	-0.176	(-9.00)	0.133	(7.70)
$PAS_{AVERAGE}$	0.426	(10.39)	0.500	(10.90)	0.287	(9.61)	-0.139	(-10.01)	-0.135	(-9.24)	0.068	(5.72)
$ACT_{AVERAGE}$	1.095	(31.42)	1.223	(28.57)	0.701	(28.75)	-0.354	(-27.71)	-0.320	(-27.68)	0.250	(20.46)
$PAS_{SKEPTIC}$	1.004	(17.88)	1.125	(14.80)	0.589	(12.77)	-0.343	(-12.60)	-0.337	(-10.12)	0.094	(2.67)
$ACT_{SKEPTIC}$	1.144	(40.63)	1.488	(38.74)	0.912	(37.27)	-0.424	(-32.00)	-0.413	(-27.42)	0.327	(18.36)
MORNING	70.855	(155.69)	61.314	(120.08)	46.033	(127.09)	39.793	(107.49)	45.930	(119.14)	62.793	(162.97)
EVENING	-2.838	(-14.03)	1.891	(8.59)	-2.470	(-14.47)	-20.804	(-128.23)	-36.713	(-191.97)	-50.493	(-248.52)
VOLUM_1H	0.122	(146.83)	0.115	(124.50)	0.121	(183.03)	0.052	(91.51)	-0.006	(-9.73)	0.011	(19.78)
VOLUM_10M	0.202	(89.38)	-0.102	(-43.03)	-0.289	(-162.64)	0.130	(67.40)	0.499	(219.85)	0.518	(243.25)
INVENTORY	-0.007	(-27.33)	-0.008	(-25.80)	-0.005	(-22.69)	-0.001	(-5.92)	-0.002	(-10.40)	-0.004	(-17.84)
Adjusted R^2	0.498		0.277		0.229		0.192		0.376		0.463	
HYPOTHESIS	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**
$PAS_i = ACT_j, \forall\ i,j$	124.40	<.0001	115.61	<.0001	117.64	<.0001	99.12	<.0001	77.35	<.0001	103.85	<.0001
$PAS_{SNEAKY} = PAS_{SKEPTIC}$	0.24	0.6232	0.14	0.7067	0.06	0.8112	0.58	0.4453	0.65	0.4203	0.01	0.9058
$PAS_{SNEAKY} = PAS_{AVERAGE}$	36.10	<.0001	25.91	<.0001	16.26	<.0001	16.26	<.0001	15.88	<.0001	0.48	0.4893
$PAS_{AVERAGE} = PAS_{SKEPTIC}$	71.14	<.0001	50.73	<.0001	31.08	<.0001	45.36	<.0001	31.37	<.0001	0.48	0.4899
$ACT_{SNEAKY} = ACT_{SKEPTIC}$	30.09	<.0001	40.89	<.0001	43.78	<.0001	54.83	<.0001	44.89	<.0001	34.46	<.0001
$ACT_{SNEAKY} = ACT_{AVERAGE}$	41.33	<.0001	99.36	<.0001	125.41	<.0001	102.21	<.0001	99.46	<.0001	65.65	<.0001
$ACT_{AVERAGE} = ACT_{SKEPTIC}$	1.50	0.2209	26.43	<.0001	44.93	<.0001	17.00	<.0001	27.23	<.0001	14.12	0.0002
Volatility												
INTERCEPT	0.0003	(9.54)	0.0002	(8.99)	0.0001	(6.66)	0.0001	(12.40)	0.0002	(16.55)	0.0003	(17.81)
PAS_{SNEAKY}	4.37	(3.60)	6.70	(3.73)	5.45	(3.83)	-3.96	(-4.22)	-4.80	(-4.11)	-2.09	(-3.38)
ACT_{SNEAKY}	1.12	(1.36)	7.90	(7.14)	4.19	(5.58)	-4.67	(-8.32)	-6.59	(-9.07)	-3.22	(-6.46)
$PAS_{AVERAGE}$	-6.37	(-5.44)	0.56	(0.49)	0.59	(0.81)	-5.46	(-9.55)	-7.34	(-9.95)	-7.23	(-10.25)
$ACT_{AVERAGE}$	15.32	(14.60)	26.87	(21.96)	16.23	(20.47)	-8.64	(-19.98)	-8.53	(-7.58)	1.20	(2.18)
$PAS_{SKEPTIC}$	-5.23	(-1.25)	1.26	(0.37)	1.00	(0.45)	-12.70	(-10.31)	-19.00	(-11.44)	-22.60	(-10.65)
$ACT_{SKEPTIC}$	41.97	(13.91)	53.20	(21.86)	31.96	(18.45)	-7.87	(-8.66)	-10.70	(-20.08)	13.28	(8.28)
MORNING	3160.00	(10.92)	830.00	(7.27)	-200.00	(-5.67)	760.00	(10.46)	1310.00	(10.80)	830.00	(5.50)
EVENING	1730.00	(20.43)	2040.00	(41.29)	1370.00	(37.42)	-85.10	(-2.93)	-400.00	(-9.84)	-200.00	(-4.52)
VOLAT_1H	0.08	(4.47)	0.05	(4.50)	0.04	(4.53)	0.03	(4.49)	0.04	(4.44)	0.05	(4.45)
VOLAT_10M	0.01	(0.29)	-0.01	(-0.67)	-0.03	(-2.50)	-0.01	(-0.63)	0.00	(0.11)	0.00	(0.05)
INVENTORY	-0.76	(-9.13)	-0.67	(-13.16)	-0.34	(-9.06)	-0.30	(-9.60)	-0.53	(-13.50)	-0.82	(-15.95)
Adjusted R^2	0.065		0.041		0.031		0.036		0.040		0.039	
HYPOTHESIS	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**	**Wald**	**p-value**
$PAS_i = ACT_j, \forall i,j$	133.99	<.0001	221.93	<.0001	175.73	<.0001	30.75	<.0001	42.19	<.0001	118.62	<.0001
$PAS_{SNEAKY} = PAS_{SKEPTIC}$	47.66	<.0001	8.50	0.0035	9.51	0.002	1.98	0.1597	3.60	0.0577	35.39	<.0001
$PAS_{SNEAKY} = PAS_{AVERAGE}$	5.13	0.0236	2.08	0.1494	2.89	0.0892	33.74	<.0001	51.93	<.0001	92.15	<.0001
$PAS_{AVERAGE} = PAS_{SKEPTIC}$	0.09	0.7675	0.04	0.8389	0.03	0.8553	37.77	<.0001	55.08	<.0001	64.97	<.0001
$ACT_{SNEAKY} = ACT_{SKEPTIC}$	108.89	<.0001	137.55	<.0001	121.94	<.0001	31.94	<.0001	1.92	0.1662	33.29	<.0001
$ACT_{SNEAKY} = ACT_{AVERAGE}$	155.06	<.0001	279.93	<.0001	210.07	<.0001	8.33	0.0039	21.22	<.0001	86.67	<.0001
$ACT_{AVERAGE} = ACT_{SKEPTIC}$	84.51	<.0001	108.36	<.0001	80.59	<.0001	0.83	0.3623	4.03	0.0447	65.45	<.0001

Table 6 Daily impact of different types of market makers

This table reports the estimation of the specification:

$$VOLAT_t = INT. + \Sigma_i \beta_i X_{inf,i,t} + \delta C_t + \varepsilon_{it}$$

where $VOLAT_t$ is the *daily* volatility of the each bond, $X_{inf,i,t}$ is the total *informed* trading originated by the dealer of class I and C_t represents a control variable. We consider two alternative specifications. In the first ones we use lagged variables to control for autocorrelation. The control variables are: the lag of the dependent variable *(LAG(VOLAT.))* and the lag of the implied volatility of options on the futures on the BTP bonds (*LAG(IV)).* In the second specification, we correct the residuals assuming an autocorrelation structure up to the third lag. In both cases, we use a weighted least-square estimator. 7,788 observations are used. Estimates for trade variables are multiplied by 100,000.

Reaction-based classification 1

	Specification 1		Specification 2	
Variable	Value	t-stat.	Value	t-stat.
INTERCEPT	-0.005	(-1.40)	0.068	(49.00)
AVERAGE	-1.441	(-3.89)	-5.028	(-9.13)
WORRIED	-0.065	(-0.12)	2.524	(2.84)
SCARED	2.494	(5.55)	7.290	(8.32)
LAG(VOLAT)	0.815	(103.64)		
LAG(IV)	0.002	(4.87)		
Adjusted R^2	0.3772		0.2967	
	Wald	p-value	Wald	p-value
ALL EQUAL	44.98	<0.0001	139.54	<0.0001
CONFIDENT =AVERAGE	3.02	0.0823	45.67	<0.0001
CONFIDENT =SCARED	44.06	<0.0001	112.48	<0.0001
AVERAGE =SCARED	7.56	0.0006	10.31	0.0013

Reaction-based classification 2

	Specification 1		Specification 2	
Variable	Value	t-stat.	Value	t-stat.
INTERCEPT	-0.006	(-1.90)	0.068	(48.67)
DUMB	-0.917	(-3.34)	-3.022	(-5.33)
AVERAGE	1.570	(2.89)	4.839	(4.53)
SMART	1.152	(2.82)	5.617	(5.64)
LAG(VOLAT)	0.810	(102.02)		
LAG(IV)	0.002	(5.42)		
Adjusted R^2	0.371		0.30	
	Wald	p-value	Wald	p-value
ALL EQUAL	31.19	<0.0001	94.02	<0.0001
DUMB =AVERAGE	11.49	0.0007	39.46	<0.0001
DUMB =SMART	19.34	<0.0001	51.49	<0.0001
AVERAGE =SMART	0.23	0.6334	0.19	0.6592

Strategy-based classification

	Specification 1		Specification 2	
Variable	Value	t-stat.	Value	t-stat.
INTERCEPT	-0.017	(-3.94)	0.070	(44.39)
SNEAKY	2.396	(5.98)	5.760	(7.79)
AVERAGE	-0.253	(-1.26)	-0.004	(-0.01)
SKEPTIC	-3.525	(-3.20)	-12.270	(-7.24)
LAG(VOLAT)	0.705	(68.94)		
LAG(IV)	0.004	(8.25)		
Adjusted R^2	0.3477		0.2852	
	Wald	p-value	Wald	p-value
ALL EQUAL	35.57	<0.0001	129.58	<0.0001
SNEAKY =AVERAGE	21.24	<0.0001	49.33	<0.0001
SNEAKY =SKEPTIC	23.85	<0.0001	110.07	<0.0001
AVERAGE =SKEPTIC	7.51	0.0061	52.18	<0.0001

Official classification

	Specification 1		Specification 2	
Variable	Value	t-stat.	Value	t-stat.
INTERCEPT	-0.028	(-5.08)	0.071	(31.66)
SPECIALIST	1.810	(4.11)	1.226	(2.15)
ORD. MM	2.776	(3.25)	1.411	(1.86)
ORD. DEALER	0.115	(0.19)	-0.941	(-1.20)
LAG(VOLAT)	0.507	(51.51)		
LAG(IV)	0.006	(11.07)		
Adjusted R^2	0.3102		0.2780	
	Wald	p-value	Wald	p-value
ALL EQUAL	6.59	0.0370	4.76	0.0924
SPECIALIST =ORD. MM	1.04	0.3076	0.04	0.8449
SPECIALIST =ORD. DEALER	2.82	0.0932	3.14	0.0765
ORD. MM =ORD. DEALER	6.53	0.0106	4.56	0.0328

Table 7 Market makers' profits.

This table reports the descriptive statistics of the profits disaggregated by the type of intermediated market maker (Panel A) and statistical tests of the difference between the profits (Panel B). Profits are defined as total profit (both from active and passive trade) of all the trades that take places within 10 minutes after originating transaction. The profits is constructed as the product between the quantity transacted and the difference between the price at the end of the day and the price at which the transaction is executed (positive in case of "buy" and negative in case of "sell"). Transaction in thinly traded bonds (less than 25 transaction per day), and transactions within 10 minutes of the closing price were excluded. Panel B reports both mean test (T-test) and median test (Wilcoxon Two-Sample Test) of the difference between profits.

Panel A: Descriptive Statistics

	N	MEAN	MEDIAN	STD DEV	SKEWNESS	KURTOSIS
OVERALL	936275	0.024%	0.000%	4.609%	0.00	83.76
Official classification						
SPECIALIST	502708	0.024%	-0.005%	4.995%	-0.30	80.44
ORD. MM	433567	0.024%	0.000%	4.284%	0.62	73.64
Strategy-based classification						
SNEAKY	215956	-0.001%	0.000%	5.298%	-0.58	75.91
AVERAGE	627137	0.011%	0.000%	4.365%	0.19	91.25
SKEPTIC	93182	0.174%	-0.054%	4.553%	0.89	44.44
Reaction-based classification 1						
CONFIDENT	248798	-0.034%	0.000%	4.676%	-0.71	89.98
AVERAGE	312280	0.013%	0.000%	4.393%	-0.10	77.68
SCARED	375197	0.062%	-0.049%	4.745%	0.37	84.42
Reaction-based classification 2						
DUMB	333355	0.004%	0.000%	4.194%	-1.84	122.57
AVERAGE	306999	0.023%	0.000%	4.950%	0.24	67.08
SMART	295921	0.035%	0.000%	4.697%	0.99	74.75

Panel B: Statistical tests of the difference in profits

	T-test				**Wilcoxon Two-Sample Test**			
	t value	**prob>|t|**	**t value**	**prob>|t|**	**Z**	**prob<Z**	**Z**	**prob<Z**
Official classification								
	ORD. MM				ORD. MM			
SPECIALIST	0.06	0.9485			1.62	0.0525		
Strategy-based classification								
	AVERAGE		SKEPTIC		AVERAGE		SKEPTIC	
SNEAKY	0.97	0.3343	9.34	<0.0001	2.65	0.0041	14.06	<0.0001
AVERAGE			10.29	<0.0001			12.59	<0.0001
Reaction-based classification 1								
	AVERAGE		SCARED		AVERAGE		SCARED	
CONFIDENT	3.86	0.0001	7.91	<0.0001	1.61	0.0542	5.66	<0.0001
AVERAGE			4.43	<0.0001			5.41	<0.0001
Reaction-based classification 2								
	AVERAGE		SMART		AVERAGE		SMART	
DUMB	1.59	0.1109	2.73	0.0064	1.97	0.0242	3.52	0.0002
AVERAGE			1.00	0.3181			0.58	0.2793

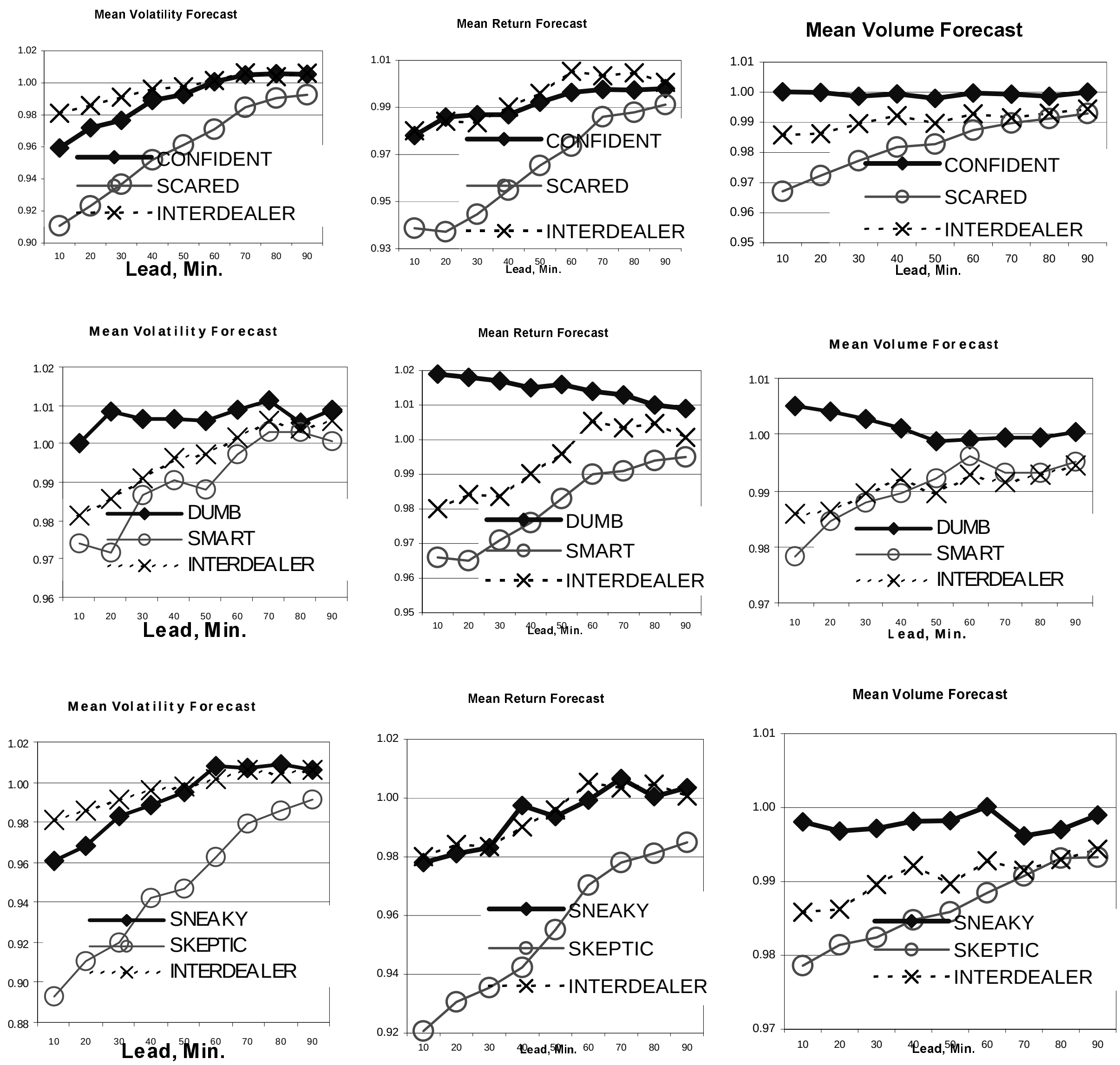

Figure1: Mean of the ratio of the mean-square forecasting error of one-step ahead VAR forecasts based on the trades of i^{th} class of market makers over the mean square forecasting error of one-step ahead VAR forecasts based on the total trade. The forecast is performed for 10-min volatility, returns and volume. In total, 60,722 forecasts have been used. The classification is the strategy-based classification.