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Abstract

European government bond market segmentation has not been extensively investigated. I contribute to this scant literature by studying the market microstructure of the Italian government bond market, the largest one in the eurozone. Using a sequential trade model, I analyze the probability of informed trading (PIN) in the parallel trading of the same bond on two secondary electronic platforms: the inter-dealer MTS and the dealer-to-customer BondVision; an aspect that has never been investigated before. I find that the PIN is significantly lower in the dealer-to-customer segment than in the inter-dealer one.

JEL classification: C51; G10; G14

Keywords: Market microstructure; Informed trading; Government bonds

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1 Introduction

In recent years, the organization of securities trading has notably changed. Trading no longer takes place in a physical location, direct dealing between dealers keeps diminishing, while more and more transactions are executed via electronic trading platforms. This is happening to a greater extent in the fixed income markets. The advent of electronic trading has dramatically affected the functioning of fixed income markets, mainly reducing the costs of transacting and obtaining information, making the execution of transactions quicker and automating the settlement procedures.

Government bonds have traditionally been the dominant segment of the euro area bond market (Biais et al., 2006). According to Persaud (2006), in the United States, electronic government bond trading represents 98 percent of all *on-the-run* volumes, whereas in Europe, it amounts to 75% [80% according to The Bond Market Association and 70% according to Celent Communications (Casey and Lannoo, 2005)].[1]

In the last decade, there has been an increasing number of researchers analyzing the functioning of the European electronic government bond market. I contribute to this growing literature studying the market microstructure of the long-term secondary Italian government bonds. In terms of the composition of the government debt instruments, around 70% are long-term government bonds (Lojsch et al., 2011). With an outstanding amount of roughly €1.6 trillion in 2011, the Italian government bond market is the third largest in the world after the U.S. and Japan and the largest one in the eurozone, followed by Germany and France.

In particular, I analyze the parallel trading of ten-year government bonds on two electronic trading platforms – an inter-dealer platform – MTS – and a dealer-to-customer one – BondVision. I investigate whether the probability of informed trading (PIN) is related to the different transparency requirements of these two platforms.

[1] A possible explanation for this discrepancy is the concern over liquidity that European market participants could have, since only one specific platform (MTS) dominates, whereas in the U.S. there are variety of different trading platforms.

The PIN is considered an appropriate measure of asymmetric information also in the context of the bond market. Even if the type of private information in the government bond market is diverse from that in the stock market, many studies have shown its existence also in this setting. Indeed, the presence of heterogeneous information in this framework can be thought of as a different skill to interpret the same publicly available information (Green, 2004) or as dealers' private access to customers order flows (Lyons, 2001). In fact, if private information is defined as in Ito et al. (1998), i.e., as anything that is not common knowledge and that is price relevant, there is likely private information also in the bond market. Some dealers may have private information in the more traditional meaning of the word (i.e., privately observing their client's order flow they infer valuable information to forecast future prices). Others will trade only on the basis of their subjective evaluations and different abilities in interpreting past economic data or in understanding the current state of the economy (Brandt and Kavajecz, 2004).

The literature on government bonds has been focused only on the more liquid inter-dealer section of the market, almost ignoring the dealer-to-customer segment. Other papers on parallel bond trading include Drudi and Massa (2005) and Dunne et al. (2008). Drudi and Massa (2005) analyze the behavior of investors simultaneously operating on the primary and secondary market, providing evidence of price manipulation in the more transparent secondary market when the less transparent primary market is open.[2] Dunne et al. (2008) consider the interaction between the inter-dealer and the dealer-to-customer segments of the European sovereign bond market, developing a model to understand the quote dynamics in both segments, as well as their interrelationship.

However, government bonds have traditionally been divided into an inter-dealer segment and a dealer-to-customer segment. The main contribution of this paper is to investigate the parallel trading on these two secondary electronic platforms. I examine on which platform, characterized by different transparency requirements, the PIN is higher, filling

[2]The authors consider the period before 1997, when market makers where not anonymous.

a gap in the market microstructure literature on the European government bond market.

The term transparency refers to pre-trade transparency (i.e., information about quotes and/or orders), post-trade transparency (i.e., information about prices and volumes), and anonymity (i.e., information on pre- and/or post-traders' identity). Under full transparency, all relevant pre- and post-trade information is publicly and timely transmitted to all market participants.

MTS provides extensive pre-trade transparency, making the order book available to all market participants; however, the trader identities are not displayed, foreseeing pre-trade anonymity. Transaction prices and volumes are instantaneously reported to all market participants providing full post-trade transparency; nevertheless, since the majority of participants uses the Central Counterparty (CCP) system, there is also post-trade anonymity.

On BondVision, there is not a proper book and, although BondVision' participants can see the prices in the MTS book, these prices are not executable. In terms of post-trade transparency, information about trades, prices, and quantities executed is available to market participants only at the end of the day and the traders' identities are known only to the market makers involved in the auction.

Changing the balance between transparency and opacity may considerably influence information asymmetry in the markets. Transparency is necessary to ensure that the level, type, and distribution of information is optimal to promote competition, fairness, and investors' protection. Opacity is needed for the ongoing participation of both end-customers and liquidity providers (Casey, 2006).

There is an extensive literature on how different market designs may impact the presence of informed trading. The idea is that informed traders prefer anonymous trading systems because they do not have to publicly disclose their trading needs; in fact, market participants would be more able to infer the probability of informed trading by observing traders' identity. However, the empirical evidence is mixed.

Barclay et al. (2003) find that anonymous markets attract informed traders and con-

sequently lead to price discovery. Foucault et al. (2007) and Comerton-Forde and Tang (2009) document, in their event studies, an improvement in market liquidity when exchanges adopt a more pre-trade anonymous market structure for the Euronext Paris and the Australian Stock Exchange, respectively. Rindi (2008) shows, with a theoretical model, that if information acquisition is endogenous (e.g., traders become informed through research), as in the bond market, anonymity increases the incentive to acquire such information, consequently augmenting the number of informed traders. The additional liquidity supplied by informed traders offsets the reduction in liquidity supplied by uninformed traders. Grammig et al. (2001) and Theissen (2003) report that market anonymity and informed trading are positively interrelated: an increase in anonymity should lead to an increase in informed trading. I find empirical evidence that the PIN is greater in the anonymous inter-dealer segment of the market, supporting the view that informed traders prefer an anonymous environment.

The remainder of this paper is organized as follows. In Section 2, I describe the institutional environment of the MTS and BondVision platforms. In Section 3, I discuss the data. In Section 4, I describe the model. Section 5 contains the methodology, the empirical results, and some robustness checks of the model specification. Concluding remarks are in Section 6.

2 Institutional environment

Now I briefly illustrate the microstructure and the functioning of the two platforms under investigation. Some market rules have now changed, thus the description refers to the rules in use during the sample period examined. Nevertheless, I also discuss the current rules where appropriate.

2.1 MTS

MTS (Mercato Telematico dei Titoli di Stato) is a wholesale screen-based regulated electronic market for government bonds and other fixed income securities. It was first introduced in Italy in 1988 and it is supervised by the Italian Treasury, the Bank of Italy, and CONSOB.[3]

BeringPoint (2005) estimates that around 75% of inter-dealer trades takes place on the MTS platform, while Persaud (2006) reports a figure of roughly 72%. With an average of more than 1,000 daily trades, MTS is the the leading market in Europe for the electronic trading of fixed income securities (Celent, 2012).[4]

During the last two decades, the MTS platform has been affected by many changes, the most important, in chronological order, are: i) the introduction of specialists in 1994, in order to enhance liquidity; ii) the privatization into MTS S.p.A., which took place in 1997 when a number of banks became its shareholders;[5] and iii) the introduction of full anonymity of traders in 2003. In 1999, with the introduction of the euro as the single accounting currency, EuroMTS was created. Ever since, fixed income securities can be traded not only on a domestic platform (e.g., MTS Italy) but also on a European one; on

[3]Commissione Nazionale per le Società e la Borsa, the supervisory authority for the Italian financial products market.

[4]Other multi-dealer platforms trading government bonds in Europe include BrokerTec and Eurex Bonds (for Austria, Denmark, Finland, Germany, and the Netherlands markets only).

[5]For what concern the shareholders' rights, no single bank has more than 5% of its voting rights. A list of these financial institutions is available on the MTS website, under the heading "shareholders' institutions."

the latter, only highly liquid securities can be traded.[6] Although all MTS platforms share the same technology, each has its own rules and market participants. Nevertheless, traders who can trade on both local and EuroMTS platforms ensure that no price discrepancies occur between the two trading platforms when trading the same bond (Baker and Kiymaz, 2013). Table A.1 in the Appendix lists the most important changes that have taken place since its creation until 2004.

MTS is divided into two sections: MTS Cash, where bonds are exchanged for cash, and MTS Repo for repurchased agreements. On the MTS Cash segment, there are two types of market participants: market makers and dealers. The former must satisfy strictly requirements in terms of trading volumes and net asset values and post bid and ask quotes for a given number of securities assigned to them. The latter are market takers who do not have any market making obligation; they simply send orders for trading at market makers' available quotes. Since market makers, unlike dealers, may also formulate proposals on any other tradable products, and issue orders for proposals made by other market makers, they can both act as price makers and as price takers.

Within the group of market makers, for the purpose of public debt management, the Italian Ministry of Economy and Finance selects a list of so-called specialists, who have to satisfy more stringent requirements in terms of participation in the secondary market. In consideration of these obligations, they receive some privileges, such as the exclusive right to participate in supplementary and buy-back primary auctions. The specialists' market share on the wholesale regulated secondary market was around 82% in 2003 and greater than 90% at the beginning of 2007, according to Nardelli (2003) and Di Veglia (2007), respectively.

There are precise rules governing the functioning of MTS. With the introduction of a "liquidity pact" in 1999, MTS' market makers are required to post buy and sell quotes for a minimum size (proposals must be formulated for a minimum lot of €2.5 or €5 million

[6]MTS has successfully launched also outside the euro area, e.g., MTS Japan Ltd. and MTS Israel in 2006. It is currently available in more than 30 markets, including the U.S..

depending on the instrument traded), within a pre-specified maximum spread according to their liquidity and maturity (it is higher for assets with a longer maturity) and for a minimum number of hours each day (at least five hours per day). This was the set of rules in use before 2007. However, since the inception of the liquidity crisis, MTS introduced more flexible market makers' quoting commitments, which require average quoting times and average spreads that must be in line with market averages computed across all market makers. The minimum trading quantity is currently €500,000.

MTS works as a limit order book. The quoted proposals are firm, immediately executable, and aggregated in an order book, which displays bid/offer prices with the related quantities. Trades are executed in chronological order and orders are automatically completed at the *best* quoted price. The trading platform provides detailed real-time screen-based information to all market participants, who can easily know the state of the market and observe the order flow (i.e., the sequence of buys and sells occurring throughout the day).[7]

Official trading hours go from 8:15am to 5:30pm Central European Time (CET). However, there is also a *pre-market* phase (7:30am-8:00am CET), during which market makers can only see their own proposals and input, modify, suspend, and reactivate their proposals; and a *preliminary* phase (8:00am-8:15am CET) during which the auto-matching of proposals is not active.

On MTS, market makers insert a proposal on the Best Page, which shows the best bid-ask spread together with its aggregate quantity for all products. Market participants select the bid or ask price depending on whether they want to sell or buy. Subsequently, the contract is finalized ("click and trade" system) and settlement instructions are automatically generated. At the end of each day, the bulletin lists, for each traded instrument, the maximum, minimum, and average weighted prices, the last trading price, and the trading volume.

[7]For a detailed description of the "live" market pages, see Cheung et al. (2005).

Before 1997, the MTS system was fully transparent, but there existed a “free-riding” problem, due to smaller market makers who mimicked the strategies of the largest ones to exploit their superior ability in trading (Albanesi and Rindi, 2000). Indeed, the reputation of a market maker has an impact on the price process (De Jong and Rindi, 2009).

Anonymity in MTS is guaranteed at least until the execution of trades, when the identity of the counterparties is revealed for clearing and settlement procedures. However, since 2003, market traders can rely on the Central Counterparty. In this case, anonymity is guaranteed also in the settlement phase and the identity of the counterparties is never revealed. During 2006, around 62% of the participants used the Central Counterparty (Arciero, 2006).

2.2 BondVision

BondVision is a multi-dealer-to-customer electronic trading platform. It is another regulated market, supervised by the Italian Ministry of Economy and Finance for the government bonds section and by CONSOB for the non-government bonds section. It was launched in 2001 “in response to continued requests from institutional investors for access to the liquidity of the MTS markets”(Cascino and Di Veglia, 2007). BondVision provides an alternative venue to transactions conducted via over-the-counter (OTC) markets. In terms of volume, inter-dealer trades are more than twice as large as dealer-to-customer trades in the government bond market (Celent, 2004).

BondVision is not a retail platform. Its customers are institutional investors, such as investment managers, hedge funds, and private banks. It allows participants, qualified as market makers, to trade directly with participants qualified as end-users. Market makers on the BondVision platform are mainly those operating on the MTS platform. Table A.3 in the Appendix lists the market makers that were active between 2004 and 2006.

BondVision works as a request-for-quote (RFQ) system; a contract is generated only as a consequence of a request from an end-user. There are three trading phases: request,

quotation, and acceptance. During the request phase, end-users can select a product and then send a RFQ concerning the price, the direction of their trade (whether they want to buy or to sell), the quantity that they want to trade, or a combination of these elements.[8] End-users can simultaneously send a RFQ to a maximum number of market makers, hence starting an auction.[9]

During the quotation phase, each market maker participating in the auction sends a responding bid or offer allowing the end-user to execute the trade at the best price. Quotations must be formulated for an amount at least equal to the minimum tradable size (it is currently €500,000; however, it was €100,000 for the sample period covered by the paper). The trading system ranks the proposals by price and, among the same price, according to the arrival time.

Market makers do not commit to providing quotes when requested and end-users are not obliged to accept the quotes they receive. A RFQ can last ninety seconds maximum; however, market makers can discretionally decide to accept it after the expiration time.[10] On the contrary, the maximum time during which quotes may be executed (live quote time) is freely chosen by each market maker; after this time has elapsed, quotes are no longer active. At the end of each trading day, any pending transaction in the system is automatically cancelled.

On BondVision there is not a proper order book as on the MTS platform. Nevertheless, BondVision's end-users can access the MTS Best Page, which displays the best bid

[8]This was the procedure in use for the sample period covered by the paper, however, as of the March 18, 2013 BondVision brochure, three different types of RFQ are currently available: "outright" if the request is for a quote for just one financial instrument; "switch" if the request is for quotes for two financial instruments, of which one is to be sold and the other is to be bought; or "butterfly" if the request is for quotes for three financial instruments, of which one is to be sold and two are to be bought or vice-versa.

[9]Each end-user is not allowed to send a RFQ to every market maker, but he can request quotes only to a certain number of them (In January 2013, the maximum number was ten; however, for my sample period, the maximum number was five, which it is also the current maximum number according to the March 18, 2013 BondVision rules). More precisely, when a new end-user joins BondVision, he gives preference towards some market makers and each market maker selected, in turn, agrees to trade with him and chooses the securities on which he is willing to offer liquidity.

[10]Each of the three phases- request, quotation and acceptance- is valid for 30 seconds. As of the April 18, 2013 rules, the total duration of a quote request is 90 seconds for "outright" and 120 seconds for "switch" or "butterfly" quote requests.

and ask prices with the related quantities in real time; however, the prices are indicative and not executable. Moreover, market makers are required to display price indications - nominative or anonymous- that must be representative of the bid and ask prices at which they would be willing to trade, which should help end-users to formulate their RFQs.

The trading time spans from 8:00am to 6:00pm CET.[11] There is also a *pre-opening* phase, during which market makers may enter quotes; however, trading is disabled and participant's own quotes are not visible to other participants.

Note that BondVision is not an anonymous venue; each market maker decides the end-users he wants to contract with. When an end-user sends a RFQ, he selects the market makers (among those with whom he is authorized to trade) and the selected market makers, in turn, know the end-user who sent them the request. Moreover, when market makers respond to a RFQ, they know how many other market makers are involved in the auction, but they can see neither their identities nor their quotes. During the last phase, the contracts concluded are regulated directly by the parties; thus there is no post-trade anonymity either.

At the end of the trading day, BondVision provides a list with at least the minimum, maximum, and weighted average price and the total negotiated amounts for each instrument traded.

3 Data

The database is composed of two datasets of fixed rate bonds (BTP - Buoni Pluriennali del Tesoro) with an original ten-year maturity.[12] One dataset contains time-stamped records of trades and proposals of BTPs traded on the cash segment of the MTS platform. The other dataset covers time-stamped records of trades and requests for quotes of BTPs traded

[11] As of March 18, 2013 BondVision's closing time is 6:45pm.

[12] The bonds in my database are: IT0003472336, IT0003618383, IT0003719918, IT0003844534, and IT0004019581.

on the BondVision platform. I consider the database as a time series, including only the number of contracts on both platforms.

The investigation sample goes from January 2004 to November 2006, for a total of 700 trading days; this choice is made to avoid potential biases in the results due to turbulences in financial markets.

A great advantage of this database is that it includes the trade direction (i.e., whether a trade was buyer or seller initiated). This is an important piece of information, since I do not have to use trading direction algorithms to infer from the data the trader initiator, thus avoiding the introduction of biases in the results due to miss-classified trades.

I divide the 700 days into five-minute intervals for a total of 75,600 observations. I remove non-valid observations from the data. Entries where either the ask or the bid price is equal to zero or the bid-ask spread is negative are deleted, as they are due to reporting errors. Furthermore, I remove all observations for the August 1-3, 2004.[13] These filters eliminate 1.57% of the raw data.

As I am interested in the parallel trading on both platforms, I consider only the trading days and the time periods common to both datasets. In fact, since BondVision closes thirty minutes after MTS, all the observations for the last half an hour are dropped. Moreover, in line with the literature (Coluzzi et al., 2008; Girardi and Impenna, 2013), I do not consider trades that happen during the first fifteen minutes of trading, since the market activity during this time is negligible. My ultimate trading time goes from 8:30am to 5:30pm CET. Finally, using the wall-clock time instead of the event time and dividing the sample into equal trading intervals, I make the two platforms more comparable.

Table A.2 in the Appendix shows descriptive statistics for the data, at five-minute and

[13]The Financial Services Authority (FSA) found that City Group Global Markets Limited (CGML) executed a trading strategy on the European government bond markets on August 2, 2004, which involved the firm building up and then rapidly exiting from very substantial long positions in European government bonds over a one-hour period. The trade caused a temporary disruption to the volumes of bonds quoted and traded on the MTS platform, a sharp drop in bond prices, and a temporary withdrawal by some participants from quoting on that platform. The FSA fined CGML on June 28, 2005, £13.9 million (€20.9 million) for Eurobond trades. Source: www.fsa.gov.uk.

daily frequencies. Figures A.2 and A.3 report the average number of trades and volume at five-minute intervals for MTS and BondVision, respectively. Note that both the number of trades, as well as traded volume per trading interval, are larger on MTS.

The Italian secondary government bond market has the largest outstanding amount in the eurozone. It had an average of around €1,218 billion in outstanding Treasury securities between 2004 and 2006, followed by Germany and France. Moreover, among the Italian debt instruments, the BTPs represent the most traded, accounting for 59.93% of the government debt.[14] Since BondVision's creation in 2001, the average daily volume is €2.5 billion, with an average size of €5 million, supporting more than 2,000 securities, with around 28 market makers and with more than 300 institutions and 2,000 traders as counterparties.[15]

Researchers who examine MTS and/or BondVision platforms study different aspects. One group focuses on the functioning of the secondary market in conjunction with important institutional changes (Scalia and Vacca, 1999; Albanesi and Rindi, 2000). Others analyze the liquidity of the market (Beber et al., 2009; Favero et al., 2010; Darbha and Dufour, 2013); the impact of macroeconomic news on returns (Paiardini, 2014); the price discovery mechanisms (Cheung et al., 2005; Dunne et al., 2007; Dufour and Nguyen, 2012; Caporale and Girardi, 2013; Girardi and Impenna, 2013); and the dynamics of sovereign spreads in bond and CDS markets (Gyntelberg et al., 2013).

4 The model

4.1 The information and trading structure

The model belongs to the class of sequential trade models that dates back to the work of Glosten and Milgrom (1985) and Easley and O'Hara (1987). Researchers who use a

[14] According to the Italian Treasury website at www.dt.tesoro.it/en.
[15] According to BondVision brochure.

sequential trade model to analyze the government bond market include Li et al. (2009), who focus on the presence of asymmetric information in the U.S. market, a decentralized market where each participant can post his own quotes and observe only a fraction of the buys and sells; and Arciero (2006), who analyses the PIN only on the inter-dealer MTS segment. In particular, I start from Easley *et al.*'s (1997b) empirical model and extend it to analyze the parallel trading of the same government bond in two markets.

The true value of the asset is represented by a random variable V_i whose value is revealed at the end of the day. The trading period is a trading day, indexed by $i \in [1, I]$. Each trading day, before trading begins, nature selects whether an information event takes place. Information events on different days are assumed to be independent. The choice of a trading day as a trading period is certainly arbitrary, since prices could adjust to new information faster and new events could happen more frequently than once a day. However, as illustrated by Easley et al. (1997b), what is important for the analysis is the arrival of new information at discrete time intervals. Moreover, the study of event uncertainty on price changes and the market maker's learning process is simplified using the fiction of a trading day, assuming that information events occur only between trading days (Easley and O'Hara, 1992).

Each trading day is divided into trading intervals of a given length; time within the trading day is discrete and it is indexed by $t \in [0, T]$. If an information event occurs, there is the arrival of a signal (Ψ) about (V_i); this happens with probability α, where $0 < \alpha < 1$. The type of signal can be high (H) in the case of good news (g), with probability $(1-\delta)$, or low (L) in the case of bad news (b), with probability δ, where $0 < \delta < 1$. If no new information occurs, there is no signal, $\Psi = 0$, and a no-event day happens with probability $(1-\alpha)$.

Therefore, if an information event occurs, the value of the asset conditional to good news is $\overline{V}_i = E[V_i|\Psi = H]$, to bad news is $\underline{V}_i = E[V_i|\Psi = L]$. The value of the asset if no news occurs is $V_i^* = \delta \underline{V}_i + (1-\delta)\overline{V}_i$, assuming $\underline{V}_i < V_i^* < \overline{V}_i$ (Easley and O'Hara, 1992).

What I have described so far is the *information process*, that happens at the beginning of each trading day, reflecting the assumption that information events occur only between trading days. This is followed by the *trader selection process*, which describes the traders' behaviour during each information state. This process is repeated at each trading interval, throughout the trading day (Easley et al., 1997b).

At every interval a trader is selected on each platform. There are two types of traders: informed and uninformed. Informed traders know whether an information event took place and trade accordingly to the true value of the asset. Uninformed traders do not know whether an information event happened nor the true value of the asset.

If an information event occurs, an informed trader is selected with probability μ_M on the inter-dealer platform and μ_B on the dealer-to-customer platform. Similarly, an uninformed trader is selected with probability $(1-\mu_M)$ on MTS and $(1-\mu_B)$ on BondVision. If no information event occurs, all traders are uninformed. The probability of an uninformed trade is ε_M and ε_B on MTS and BondVision, respectively. Similarly, the probability of a no-trade is given by $(1-\varepsilon_M)$ and $(1-\varepsilon_B)$. Informed traders will buy the asset in the case of good news and will sell it in the case of bad news, both with probability one.

If uninformed traders have chosen to trade, they will buy with probability η_M on the inter-dealer platform and η_B on the dealer-to-customer one; they will sell with probability $(1-\eta_M)$ and $(1-\eta_B)$ on the MTS and BondVision platforms, respectively.[16]

Thus, during a newsworthy day, while an informed trader will always trade, an uninformed trader will trade only for portfolio balancing purposes. If no information occurs,

[16]This is different from Easley *et al.*'s (1997b) model, where uninformed traders buy and sell with the same probability. However, in principle, there is no reason to assume that they must be the same. Firstly, the type of traders, on both platforms, are heterogeneous, thus their portfolio rebalancing motivations to trade could be very different. Secondly, the arrival of uninformed traders may differ under diverse economic conditions (i.e., during a credit crunch); for example, there could be an increase in sell orders because traders have to satisfy their liquidity needs. Under these circumstances, as pointed out by Lin and Ke (2011), assuming the same probability for buying and selling may lead to an overestimation of PIN. Finally, the likelihood ratio test in the robustness checks section clearly rejects the restricted model specification, where the probabilities of uninformed buys and sells are the same, in favour of the unrestricted one where these two probabilities are allowed to differ.

all trades are uninformed. As in Grammig et al. (2001), I do not model traders' market choice, instead, we assume that the arrival rates of informed and uninformed traders in both markets is given; although there are no reasons to set equal arrival rates in both markets.

The market maker knows that there are informed and uninformed traders in the market, but he does not know the type of trader he is trading with. Market makers are risk-neutral and act competitively. They know that the order flow is related to the true value of the asset, and they use this indirect evidence to infer its underlying value. Observing a buy, the market maker can infer that the trade comes either from an informed trader, who has good news about the traded asset, or from an uninformed one. Similarly, when he observes a sell, he infers that the order comes either from an informed trader who knows bad news, or from an uninformed one. Throughout the trading day, the market maker uses Bayes's rule to update his beliefs about the bid-ask quotes, observing the order flow.[17] Competition among the market makers drives profit to zero.

Event uncertainty, at the beginning of each trading day, implies that there could be no-trade intervals. In this perspective, market makers learn not only from trades but also from the lack of trades. Indeed, as informed traders always trade (according to the signal), all no-trading intervals happen because an uninformed trader decides not to trade (O'Hara, 1998). Given that, there might be a negative correlation between the probability of a no-trade interval and that of a newsworthy event. However, it is not possible to gather the absence of any news event simply from a no-trade observation. In fact, this can occur both when there has not been an information event and when a trader has decided not to trade for portfolio reasons; although, looking at the probabilities, a no-trade outcome is more likely to occur when there is no new information (Easley and O'Hara, 1992).

The overall decision process is shown in the tree diagram in Figure 1.

For each trading interval t, I can have the following set of pairs of outcomes of the

[17] For a more detailed discussion, see O'Hara (1998), pp. 78-82.

trading process:

$$\theta_t \in \{(B_{M,t}, B_{B,t}), (S_{M,t}, S_{B,t}), (B_{M,t}, S_{B,t}), (S_{M,t}, B_{B,t}), (B_{M,t}, NT_{B,t}), (S_{M,t}, NT_{B,t}), (NT_{M,t}, B_{B,t}), (NT_{M,t}, S_{B,t}), (NT_{M,t}, NT_{B,t})\}.$$

These pairs of outcomes represent all the possible combinations of buys, sells, and no-trade intervals on the two platforms, that could happen at each time interval t. $B_{M,t}$ and $B_{B,t}$ designate a buy trade on MTS and on BondVision, respectively, $S_{M,t}$ and $S_{B,t}$ indicate a sell trade on MTS and on BondVision correspondingly, and $NT_{M,t}$ and $NT_{B,t}$ denote no-trade respectively on the MTS and on BondVision platforms.

The same bond is traded by a market maker who has access to both platforms. He will extract information from the above outcomes, i.e., at each trading interval he could observe a buy on MTS and a buy on BondVision or a buy on MTS and a sell on BondVision and so on. However, as in Grammig et al. (2001), while it is important for the updating process and the bid-ask prices whether the market maker is able to observe the trades only in one market or in both markets, this is irrelevant for the estimation of the parameters of the structural model. This is a consequence of the assumption of independent order arrival rates in both markets. Indeed, although traders on BondVision can see MTS prices on the MTS Best Page, they do not have access to the MTS platform.

4.2 The maximum likelihood estimation

For the empirical application of sequential trade models, neither the occurrence of information events nor the associated arrival rate of informed and uniformed traders is directly observable. However, assuming that the traders' arrival rates depend on the type of trading day, it is possible to infer information, concerning the event type and the associated arrival rates by observing the number of buys, sells, and no-trade intervals for each day.

The database contains records of the number of sells and buys; however, I have to define the no-trade intervals. For this purpose, I construct two dummy variables $NT_{M,t}$ and $NT_{B,t}$ for no-trading time intervals, one for each platform, which take value 1 if there is not a trade during a five-minute interval, and 0 otherwise.

The number of no-trade intervals varies with respect to the trading interval length chosen. Following Easley et al. (1997b), I choose five-minute intervals as a reasonable compromise between minimizing market frictions and making at least one trade feasible in each interval. Nevertheless, since any trading interval is arbitrary, as a robustness check I replicate the analysis using intervals of different lengths.

The parameter vector is: $\Omega = [\alpha, \delta, \mu_M, \mu_B, \varepsilon_M, \varepsilon_B, \eta_M, \eta_B]'$. I estimate the eight parameters of the trading process through a maximum likelihood procedure, using the structure illustrated in Figure 1.

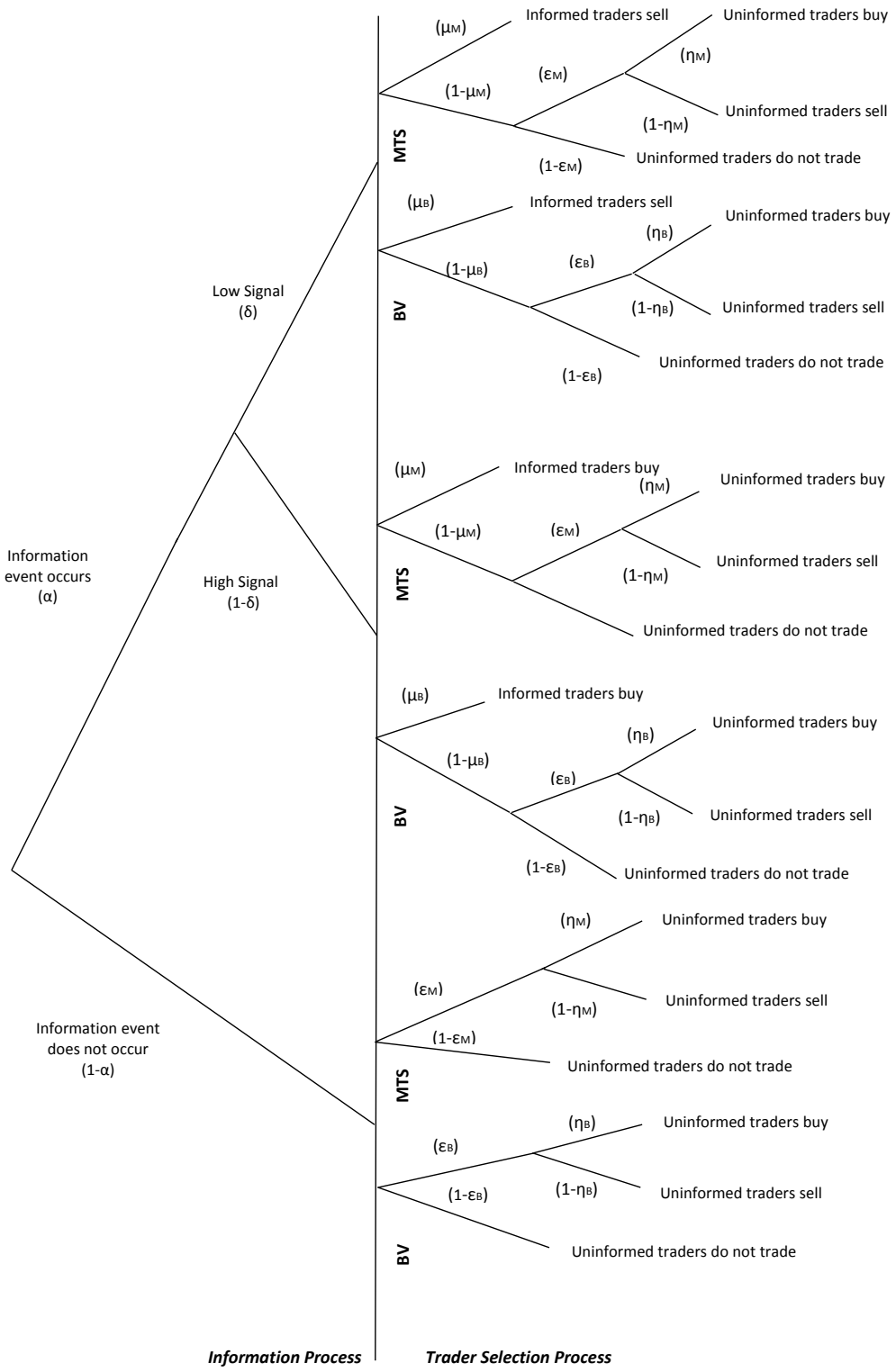
The joint daily likelihood of observing a given trade history, for both platforms, depends on whether there is news at all, and on whether the news is good or bad.

Since trading outcomes are independent, the probability of observing the possible trading outcomes on a good news day is given by:

$$\begin{aligned} & P_g\left(B_M \cap B_B \cap S_M \cap S_B \cap NT_M \cap NT_B || \overline{V}_i; \Omega\right) = \\ & \quad [\mu_M + (1-\mu_M)\,\varepsilon_M \eta_M]^{B_M} \cdot [\mu_B + (1-\mu_B)\,\varepsilon_B \eta_B]^{B_B} \\ & \quad \cdot [(1-\mu_M)\varepsilon_M(1-\eta_M)]^{S_M} \cdot [(1-\mu_B)\varepsilon_B(1-\eta_B)]^{S_B} \\ & \quad \cdot [(1-\mu_M)(1-\varepsilon_M)]^{NT_M} \cdot [(1-\mu_B)(1-\varepsilon_B)]^{NT_B}, \end{aligned} \tag{13}$$

where B_M, S_M, and NT_M are the number of buys, sells, and no-trade intervals on the inter-dealer platform occurring during a good news day i; B_B, S_B, and NT_B are the equivalents on the dealer-to-customer platform.

Figure 1: Tree diagram of the trading process



On a bad news day, the corresponding probability is given by:

$$
\begin{aligned}
&P_b\left(B_M \cap B_B \cap S_M \cap S_B \cap NT_M \cap NT_B || \underline{V}_i; \Omega\right) = \\
&\quad \left[(1-\mu_M)\,\varepsilon_M \eta_M\right]^{B_M} \cdot \left[(1-\mu_B)\,\varepsilon_B \eta_B\right]^{B_B} \\
&\quad \cdot \left[\mu_M + (1-\mu_M)\,\varepsilon_M\,(1-\eta_M)\right]^{S_M} \\
&\quad \cdot \left[\mu_B + (1-\mu_B)\,\varepsilon_B\,(1-\eta_B)\right]^{S_B} \\
&\quad \cdot \left[(1-\mu_M)\,(1-\varepsilon_M)\right]^{NT_M} \cdot \left[(1-\mu_B)\,(1-\varepsilon_B)\right]^{NT_B}.
\end{aligned}
\tag{14}
$$

Finally, on a no-event day, the corresponding probability is the following:

$$
\begin{aligned}
&P_n\left(B_M \cap B_B \cap S_M \cap S_B \cap NT_M \cap NT_B || V_i^*; \Omega\right) = \\
&\quad \left[\varepsilon_M \eta_M\right]^{B_M} \cdot \left[\varepsilon_B \eta_B\right]^{B_B} \\
&\quad \cdot \left[\varepsilon_M (1-\eta_M)\right]^{S_M} \cdot \left[\varepsilon_B (1-\eta_B)\right]^{S_B} \\
&\quad \cdot \left[(1-\varepsilon_M)\right]^{NT_M} \cdot \left[(1-\varepsilon_B)\right]^{NT_B}.
\end{aligned}
\tag{15}
$$

It is possible to derive the unconditional likelihood for one trading day combining the three conditional probabilities (13), (14) and (15), weighted by the probabilities of observing the information regimes: $\alpha(1-\delta)$ for good event days, $\alpha\delta$ if bad event days occur, and $(1-\alpha)$ for no-event days.

The unconditional likelihood for a single day i is the weighted average of expressions (13)-(15):

$$
\begin{aligned}
&P_i\left(B_M \cap B_B \cap S_M \cap S_B \cap NT_M \cap NT_B; \Omega\right) = \\
&\quad \alpha(1-\delta) \cdot P_g\left(B_M \cap B_B \cap S_M \cap S_B \cap NT_M \cap NT_B | \overline{V}_i; \Omega\right) + \\
&\quad \alpha\delta \cdot P_b\left(B_M \cap B_B \cap S_M \cap S_B \cap NT_M \cap NT_B | \underline{V}_i; \Omega\right) + \\
&\quad (1-\alpha) \cdot P_n\left(B_M \cap B_B \cap S_M \cap S_B \cap NT_M \cap NT_B | V_i^*; \Omega\right).
\end{aligned}
\tag{16}
$$

The log-likelihood for I trading days is obtained by summing the logarithms of daily likelihood contributions over the whole sample period:

$$L(\alpha,\delta,\mu_M,\mu_B,\varepsilon_M,\varepsilon_B,\eta_M,\eta_B|B_M,B_B,S_M,S_B,NT_M,NT_B) =$$
$$\sum_{i=1}^{I} ln \begin{cases} \alpha(1-\delta)\cdot P_g\left(B_M \cap B_B \cap S_M \cap S_B \cap NT_M \cap NT_B|\overline{V}_i;\Omega\right) + \\ \alpha\delta\cdot P_b\left(B_M \cap B_B \cap S_M \cap S_B \cap NT_M \cap NT_B|\underline{V}_i;\Omega\right) + \\ (1-\alpha)\cdot P_n\left(B_M \cap B_B \cap S_M \cap S_B \cap NT_M \cap NT_B|V_i^*;\Omega\right). \end{cases} \tag{17}$$

5 Empirical analysis

In this section, I perform a maximum likelihood estimation using the log-likelihood specified in Equation (17), for the sample of 700 days.

The resulting maximum likelihood estimations of the parameters for the two platforms are reported in Table 1. The results show that, during the sample period, market makers expect that an information event (α) occurs with a 37% probability.

Bad event days (δ) occur with a roughly 46% probability, thus good news days are slightly more likely than bad news days.

When an information event occurs, informed traders (μ_M) are approximately 23% on MTS and around 3% on BondVision (μ_B). This discrepancy suggests that is very unlikely to encounter an informed trader on the BondVision platform.

There is a 54% probability that an uninformed trader executes a trade on MTS (ε_M) and a value of around 14% probability that an uninformed trader trades on BondVision (ε_B).

When an uninformed trade is executed, there is a 52% probability that it is a buy on MTS (η_M) and 57% probability on BondVision (η_B).

The estimates of all parameters are accurate, as indicated by the standard errors in Table 1. The accuracy is lower for α and δ since multiple days are needed to identify the

last two parameters (Easley et al., 1997b). Overall, the evidence suggests that the maximum likelihood estimation has been successful in identifying the parameters underlying the model.

Table 1: Estimated parameters (five-minute intervals)

α	δ	μ_M	μ_B	ε_M	ε_B	η_M	η_B
0.374	0.465	0.234	0.033	0.544	0.143	0.525	0.574
(0.020)	(0.034)	(0.003)	(0.003)	(0.002)	(0.001)	(0.004)	(0.005)

The table reports the estimated parameter values at five-minute intervals. The parameters are the same as defined in the model. α is the probability of an information event; δ is the probability of bad news; μ_M and μ_B are the probabilities of informed traders on the inter-dealer and the dealer-to-customer platform, respectively; ε_M and ε_B are the probabilities that an uninformed trader trades on the inter-dealer and dealer-to-customer platforms, respectively; η_M and η_B are the probabilities that an uninformed trader buy on the inter-dealer and dealer-to-customer platform respectively. Standard errors are given in parentheses.

Finally, with the estimated parameters in Table 1, I derive the probability of informed trading on platform j, where j indicates either MTS or BondVision:

$$PIN_j = \frac{\alpha_j \mu_j}{\alpha_j \mu_j + \left(1 - \mu_j\right) \varepsilon_j}. \tag{19}$$

The probability of encountering an informed trader on the dealer-to-customer segment of the market (PIN_{MTS}) is approximately 17%, while the corresponding probability on the inter-dealer one (PIN_{BV}) is 8%. I test the nonlinear hypothesis that the probabilities of informed trading are equal on the two platforms. With a $\chi^2_{(1)}$= 124.91, the results suggest that the two values are statistically different.

The results are in line with the literature, which indicates that informed traders prefer an anonymous setting.

5.1 Robustness checks

I now perform a series of robustness checks for the model specification. First, I replicate the analysis for different no-trade time intervals. Previous studies (Easley et al., 1997a,b; Arciero, 2006) use a range of different interval lengths; to check the robustness of the results, I replicate the analysis at 8-minute, 10-minute, and 30-minute intervals. The results are in Table 2. Estimates of α and δ do not change significantly for different no-trade intervals. This is due to the fact that they measure the daily probability of an information event and a bad event, respectively. In addition, the parameters η_M and η_B do not vary with the interval length. They represent the probability that uninformed traders will buy on each platform and, given that this is a random decision, there is no reason to expect a change in their values with different trading intervals. Moreover, as for the five-minute interval estimates, the probability that an uninformed trader will buy or sell on the dealer-to-customer platform is slightly higher. The parameters ε_M, ε_B, μ_M, and μ_B exhibit an increasing path for intervals of increasing length, although the variability in μ_M is lower than in μ_B. As in Easley et al. (1997b), I can conclude that the parameter estimates do not depend on the choice of the interval length.

Second, following Grammig et al. (2001), I estimate models with different parameter restrictions. The base model (Model 1) forces α and δ to be equal on both platforms, whereas it does not impose any restriction on the order arrival rates of informed (μ_j) and uninformed traders (ε_j) and on the probability that uninformed traders buy (η_j). As explained, the type of private information in the government bond market is related to the different ability of market participants to interpret the same publicly available information. Moreover, in the model the same bond is traded on both platforms by mainly the same market makers. Therefore, deriving the probability of informed trading on a joint likelihood, setting the probability that an information event occurs (α), and the probability that it is a bad one (δ) equal on both platforms, seems the most appropriate choice.

Third, I estimate three different variations of the base model. The first variation

(Model 2) forces the probability that uninformed traders buy being equal to one-half on both platforms, $\eta_M = \eta_B = 1/2$. The second modification (Model 3) restricts all the parameters to be equal between the two platforms, imposing the joint restrictions on the informed and uninformed order arrival rates, $\mu_M = \mu_B$ and $\varepsilon_M = \varepsilon_B$. The last variation (Model 4) allows all the parameters, including α and δ, to differ on the two platforms.

Finally, I perform a series of log-likelihood ratio tests to compare the base model to the alternative model specifications. The results are reported in Table 3. I compare the base model with Model 2, which imposes to one-half the probability that uninformed traders buy on both platforms. The restricted Model 2 is rejected in favor of Model 1, indicating that this probability differs between the two platforms. Log-likelihood ratio test, which compares Model 1 to Model 3, provides clear evidence that the trading intensities are significantly different in the two trading systems. In fact, the restricted Model 3 is rejected in favor of Model 1. Lastly, in comparing the base model to the one that allows all the parameters to be different between the two platforms (Model 4), the restricted model (Model 1) is preferred.[18]

[18]Due to the high number of parameters in this last specification model, I keep the probability to buy or sell on both platforms fixed in order to reach the convergence.

Table 2: Estimated parameters for different no-trade intervals

	No-trade intervals			
Parameters	5	8	10	30
α	0.374	0.380	0.385	0.350
	(0.020)	(0.021)	(0.021)	(0.024)
δ	0.465	0.503	0.533	0.482
	(0.034)	(0.048)	(0.036)	(0.045)
μ_M	0.234	0.251	0.254	0.306
	(0.003)	(0.004)	(0.005)	(0.008)
μ_B	0.033	0.064	0.090	0.159
	(0.003)	(0.005)	(0.006)	(0.012)
ε_M	0.544	0.695	0.766	0.955
	(0.002)	(0.002)	(0.002)	(0.001)
ε_B	0.143	0.213	0.258	0.595
	(0.001)	(0.002)	(0.003)	(0.004)
η_M	0.525	0.517	0.511	0.522
	(0.004)	(0.008)	(0.004)	(0.004)
η_B	0.574	0.573	0.570	0.575
	(0.005)	(0.006)	(0.006)	(0.006)
PIN_{MTS}	0.173	0.155	0.146	0.139
	(0.008)	(0.007)	(0.007)	(0.007)
PIN_{BV}	0.082	0.109	0.129	0.100
	(0.007)	(0.011)	(0.010)	(0.010)

The table reports the estimated parameter values at 5, 8, 10, and 30-minute no-trade intervals. The parameters are those defined in the model. α is the probability of an information event; δ is the probability of bad news; μ_M and μ_B are the probabilities of informed traders on the inter-dealer and the dealer-to-customer platform respectively; ε_M and ε_B are the probabilities that an uninformed trader trades on the inter-dealer and dealer-to-customer platforms respectively; η_M and η_B are the probabilities that an uninformed trader buy on the inter-dealer and dealer-to-customer platform respectively. Standard errors are given in parentheses.

Table 3: Model specification

Model 1		Model 2		Model 3		Model 4	
α	0.374	α	0.378	α	0.364	α_M	0.547
	(0.020)		(0.020)		(0.020)		(0.181)
δ	0.465	δ	0.568	δ	0.503	α_B	0.400
	(0.034)		(0.032)		(0.034)		(0.022)
μ_M	0.234	μ_M	0.232	μ	0.170	δ_M	0.605
	(0.003)		(0.003)		(0.002)		(0.249)
μ_B	0.033	μ_B	0.038	ε	0.372	δ_B	0.540
	(0.003)		(0.003)		(0.001)		(0.033)
ε_M	0.544	ε_M	0.544			μ_M	0.093
	(0.002)		(0.002)				(0.017)
ε_B	0.143	ε_B	0.141			μ_B	0.108
	(0.001)		(0.001)				(0.003)
η_M	0.525					ε_M	0.109
	(0.004)						(1.013)
η_B	0.574					ε_B	0.113
	(0.005)						(0.001)
						η_M	0.525
							(0.004)
						η_B	0.574
							(0.005)
LR Test 1: M1 vs. M2	0.0000						
LR Test 2: M1 vs. M3	0.0000						
LR Test 3: M1 vs. M4	0.6736						

The table reports the estimated parameters for different models specifications. Model 1 is the base model, which restricts the probabilities α and δ to be equal on the two platforms, whereas the order arrival rates for informed -μ_M, μ_B- and uninformed trades-ε_M,ε_B- are allowed to differ as well as the probability that uninformed traders decide to buy (η_M, η_B). In Model 2, the probability that uninformed traders decide to buy or sell is enforced equal to one-half on both platforms. In Model 3 all parameters are restricted to be equal to between the two platforms. Finally, Model 4 allows all parameters to differ across the two trading systems. The last section of the table reports the *p*-values of likelihood-ratio tests (LR Test) for the above alternative models specifications. Since Model 1 is less restrictive than Model 2 and Model 3 but more restrictive than Model 4, a *p*-value smaller than 0.05 for LR Test 1 and LR Test 2 and larger than 0.05 for LR Test 3 support the specification of Model 1.

6 Conclusion

In this paper, I investigate the presence of asymmetric information in two secondary government bond markets. I analyze the parallel trading of Italian government bonds with a ten-year maturity (BTPs) on two secondary electronic platforms: the inter-dealer MTS and the dealer-to-customer BondVision. These two platforms differ in terms of transparency requirements.

The model allows to explain the stochastic process governing the bond prices on the basis of the number of buys, sells, and no-trade intervals occurred over a sample of 700 trading days. Asymmetric information arises since each day nature delivers a signal to the market about the true value of the asset. This signal could be good or bad and it is known only to a fraction of the traders (informed traders).

I find that the probability of informed trading on the inter-dealer segment is around 17%, whereas on the dealer-to customer one, it is roughly 8%. I also conduct some robustness checks to test the sensitivity of our findings to different model specifications and assumptions.

To the best of my knowledge, there are no other papers in the literature on parallel trading on these two platforms, thus I fill the gap in the empirical investigation of the segmentation of the European government bond market. The results are in line with the existing cited literature on the effect of the level of anonymity on informed trading, which predicts that informed traders prefer an anonymous setting.

Once the segmentation of the market into an inter-dealer and a dealer-to-customer platform is in place, it offers a variety of advantages to market participants. Dealers are better off building and maintaining a clientele who compensate them for the risk of providing liquidity in the secondary inter-dealer market; and clients are better off routing most of their order flow through one dealer because they can expect better execution (Dunne, 2007). However, there are also concerns related to the diverse trading organization of the

two market segments, in particular the absence of anonymity in the dealer-to-customer segment. In fact, the ongoing relationships with customers might limit the (short-term) price competition between dealers, and this could be a drawback, especially for smaller clients.

Despite the institutional changes in the regulations of markets currently in force, to strengthen transparency in the financial markets, there is an increasing tendency to introduce anonymity: MTS in 1997, Euronext Paris in 2001, the Tokyo Stock Exchange in 2003, Italian Stock Exchange in 2004, Australian Stock Exchange in 2005, and the Helsinki Stock Exchange in 2006. The theoretical prediction is that informed traders prefer anonymous markets, hence an increase in anonymity would lead to an increase in informed trading. Given that there is an inverse relation between adverse selection and informed trading, an increase in anonymity would increase adverse selection costs and reduce the amount of liquidity supplied by the uninformed traders. However, as pointed out by Rindi (2008), if information acquisition is endogenous, as in the bond market, anonymity increases the incentive to acquire such information, consequently increasing the number of informed traders. The additional liquidity supplied by informed traders offsets the reduction in liquidity supplied by uninformed traders.

It would be interesting to analyze whether changing the transparency requirements in the dealer-to-customer segment, introducing anonymity or allowing the customers to directly access the inter-dealer platform, would increase the presence of informed traders, hence liquidity, in the customers' segment. Such changes should be supported by an adequate participation of dealers in the inter-dealer segment, that could be negatively affected. These aspects will be the object of a future work.

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Appendix

Table A.1: Changes in the MTS organization over the last two decades

Year	Changes in market microstructure
1988	Setting up of MTS Italy Start of regular re-openings of Treasury auctions Floor to bid prices abolished for T-bills; uniform price auction introduced for other bonds
1994	Treasury starts publishing timetable of auctions Electronic bid submission at auctions Reserved re-openings for "specialists" in government securities Continuous trading on the electronic retail market
1997	Monitoring functions to the MTS management board Introduction of (ex-ante) anonymity of trades in the continuous trading market Floor to bid prices abolished fr T-bills; uniform price auction introduced for other bonds
1998	First ad-hoc re-openings of Treasury auctions
1999	Setting up of EuroMTS
2003	Introduction of full anonymity of trades with the Central Counterparty (CCP) system
2004	Setting up of NewEuroMTS

Source: MTS Brochures, Scalia and Vacca (1999) and Girardi and Piga (2007).
The table reposts the most important changes that happen on the MTS platform in chronological order since its establishment.

Table A.2: Descriptive statistics

Statistics	B_B	B_M	S_B	S_M	NT_B	NT_M
Five-minute intervals						
N	75600	75600	75600	75600	75600	75600
Mean	0.757	1.317	0.586	1.248	0.880	0.638
Variance	1.069	4.990	1.073	5.123	0.105	0.231
Minimum	0	0	0	0	0	0
Maximum	21	54	24	54	1	1
Skewness	7.930	7.243	9.753	7.175	-2.340	-0.574
Kurtosis	123.972	97.820	166.440	94.614	6.474	1.330
Q_5	0	0	0	0	0	0
Q_{25}	0	0	0	0	1	0
One-day intervals						
N	700	700	700	700	700	700
Mean	9.801	51.547	7.527	48.898	95.118	68.847
Variance	54.983	969.839	38.722	986.546	56.963	150.158
Minimum	0	1	0	1	74	26
Maximum	42	216	41	221	107	106
Skewness	1.300	1.667	1.447	1.575	-0.332	0.024
Kurtosis	5.030	7.040	6.177	6.667	2.192	3.289
Q_5	1	1	0	14	82	49
Q_{25}	4	32	3	27.5	89	61.5

B_B and B_M are the number of buys on BondVision and MTS respectively; S_B and S_M are the number of sells on BondVision and MTS respectively; NT_B and NT_M are the number of no-trade intervals on BondVision and MTS respectively. This table shows descriptive statistics for each of the mentioned variable: the mean, the variance, the minimum, the maximum, the skewness, and the kurtosis, while Q_5 and Q_{95} are the 5th and 95th percentiles.

Table A.3: Market participants on MTS and BondVision between 2004 and 2006

Financial Institutions	2004			2005			2006		
	Specialists	MTS Market Makers	BV Market Makers	Specialists	MTS Market Makers	BV Market Makers	Specialists	MTS Market Makers	BV Market Makers
Abax Bank		*			*				
ABN AMRO		*	*		*	*	*	*	*
Banca Akros		*			*				
Banca Caboto[a]	*	*	*	*	*	*	*	*	*
Banca CR Firenze	*	*			*			*	
Banca IMI	*	*	*	*	*	*	*	*	*
Banca Sella		*			*			*	
Banco Bilbao Vizcaya Argentaria		*							
Bank of America		*		*	*			*	
Barclays		*	*	*	*	*	*	*	*
BNL	*	*	*	*	*		*	*	*
BNP Paribas	*	*	*	*	*	*	*	*	*
Calyon				*	*	*	*	*	*
Capitalia	*	*	*	*	*	*	*	*	*
Citigroup	*	*	*	*	*	*	*	*	*
Credit Agricole Indosuez	*	*							
Credit Suisse	*	*	*	*	*	*	*	*	*
Deutsche Bank	*	*	*	*	*	*	*	*	*
Dresdner Bank		*	*	*	*		*	*	*
Goldman Sachs	*	*	*	*	*	*	*	*	*
HSBC				*	*	*	*	*	*
Iccrea Banca		*			*			*	
ING Bank	*	*	*	*	*	*	*	*	*
JP Morgan	*	*	*	*	*	*	*	*	*
KBC Bank		*	*	*	*			*	*
Lehman Brothers		*	*	*	*	*	*	*	*
Merrill Lynch	*	*	*	*	*	*	*	*	*
Morgan Stanley	*	*	*	*	*	*	*	*	*
MPS	*	*		*	*		*	*	
Natexis Banque Populaire		*							
Nomura		*	*	*	*	*	*	*	*
Royal Bank of Scotland								*	*
Société Générale		*	*	*	*	*	*	*	*
UBS	*	*	*	*	*	*	*	*	*
Unicredit	*	*	*	*	*	*	*	*	*
XIS Corporate and Investment Bank[b]								*	*

This table reports the list of the participants on MTS and BondVision between 2004 and 2006. Under the heading "Specialists", I list the institutions designed by the Treasury to respond to more stringent requirements in terms of market participation. Source: MTS brochures for different years.

[a] Banca Caboto became Banca IMI in October 2007.

[b] In Novemebr 2006, Natixis, a French corporate and investment bank was created from the merger of Natexis Banque Populaire IXIS Corporate and Investment Bank.

Figure A.2: Average number of trades and volume on MTS

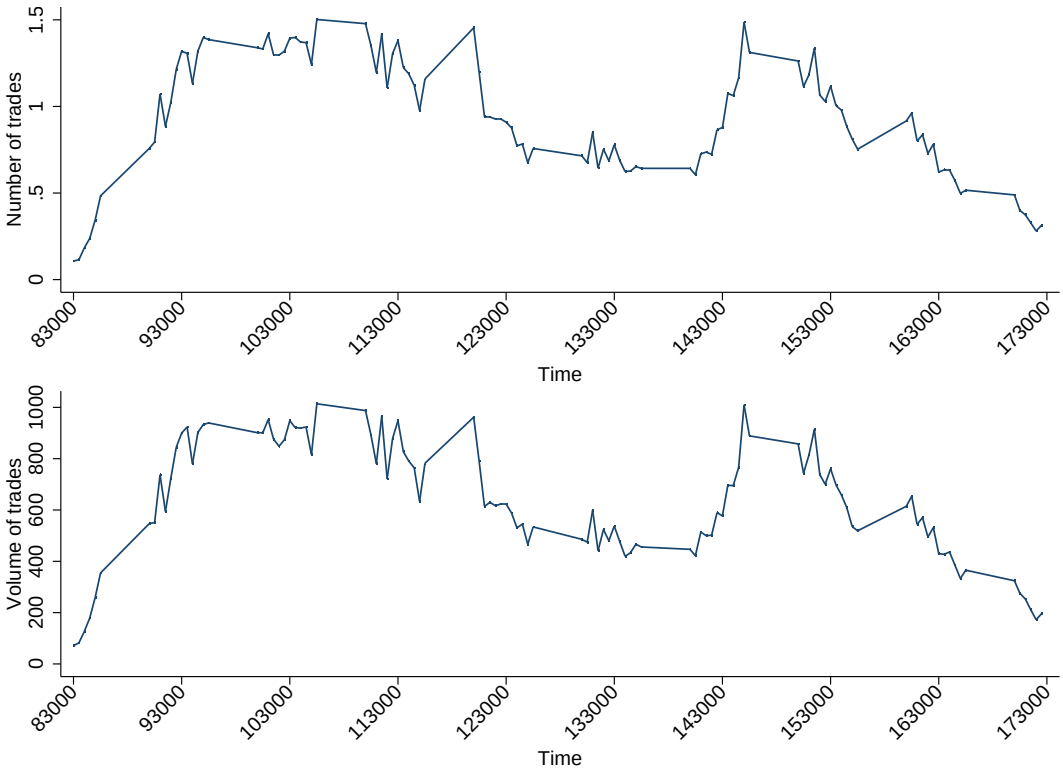

Figure A.3: Average number of trades and volume on BondVision