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Abstract

In this paper we investigate the presence of asymmetric information in the parallel trading of ten-year government fixed rate bonds (BTP) on two secondary electronic platforms: the business-to-business (B2B) MTS platform and the business-to-customer (B2C) BondVision one. The two platforms are typified by a different degree of transparency. We investigate whether the probability to encounter an informed trader on the less transparent market is higher than the corresponding probability on the more transparent one.

Our results show that on BondVision, that is the less transparent platform, the probability of encountering an informed trader is higher. Finally we perform a series of tests to check the robustness of our estimates. Two tests do not meet the hypothesis of independence. Nevertheless, these findings do not controvert the hypothesis of our model, but call for further analysis.

JEL codes: C51; G10; G14

Keywords: Market microstructure; Informed trading; Parallel trading; Transparency

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1 Introduction

Nowadays the scenario for the investors has notably changed with respect to a non so far past. The quick progresses in Information and Communication Technology have outstandingly changed the organization of securities trading in Europe and worldwide. Trading no longer takes place in a physical location, while trading floors and telephone networks are more and more moving over for transactions conducted via electronic trading platforms.

Today investors have the possibility to select among a great variety of choices what is the best suitable for their own requirements and execute their trades. Financial securities are not only traded on regulated markets but also on new electronic trade platforms, which are characterised by different levels of intermediation. There has been a notable raise in the development of these new electronic markets, where are traded securities that were already traded in non-electronic existing markets.

All these changes have driven a great increase in theoretical works concerning the analysis of market microstructure, furthermore the recent availability, at relative low costs, of high frequency datasets have contributed to a notable increase also in empirical works.

The coexistence of multiple markets for the same asset is a pervasive phenomenon; financial securities may trade simultaneously on a number of markets, so the main issue of a trader is to decide how to allocate his orders across the different trading venues. As a consequence, all these trading venues compete for order flow, so it is really important to understand how inter-market competition affects market quality. This scenario raises questions about the coexistence of markets that differ along a variety of dimensions.

There exists an extensive market microstructure literature on single markets, which analyses their characteristics, how they work and so on, however there is a scarce literature on intermarket competition, where traders can trade a same asset simultaneously on several markets and on the interactions among different market segments. Government bond market has been traditionally divided in an inter-dealer and a dealer-to-customer segment, however, economic researches, which had analysed these two dimensions, had focused their attention only on the more liquid inter-dealer segment ignoring the dealer-to-customer segment.

There is a narrow theoretical and empirical literature which had nibbled at the impact that the existence of electronic trading platform have on traditional markets and the chances of survival of both. One of the most promising approach which is catching on the literature about market microstructure and more precisely, concerning how parallel trading of a security on several markets can influence prices, is the sequential trade model. This model combines both econometric analysis and economic theory, which was initially used simply to analyse information aspects of the price discovery process on financial markets.

In a sequential trade model there are three economic agents who are in a dynamic interaction: a market maker who supplies liquidity to the market by continuously posting prices at which the security may be bought and sold, and two types of traders, who differ with respect to their information set on future price movements. In this framework the market maker sets prices without knowing whether any trader has superior information about the fundamental value of the security. The main aim of these models is to analyse the effects of asymmetric information among market participants on the outcomes of the trading process.

In this work we construct a sequential trade model to consider parallel trading on two platforms of the secondary bond markets, MTS (Mercato Telematico dei Titoli di Stato) and BondVsion, which are typified by a different degree of transparency. The Italian government bond market is one of the largest in the world. We investigate whether the probability to encounter an informed trader on the less transparent market is higher than the corresponding probability on the more transparent one.

The paper proceeds as follows. Section 2 briefly reviews sequential trade models under asymmetric information for equity and bond markets. Section 3 analyses the institutional environment. Section 4 describes the asymmetric information model used to analyse the parallel trading on the two platforms. Section 5 illustrates the database. Section 6 contains the empirical analysis. Section 7 concludes.

2 Models under asymmetric information

There are two different approaches to model sequential securities market behaviour in the presence of asymmetric information. One approach is Walrasian batch models and another is sequential trade models.

In the Walrasian approach, market makers observe the net order from traders and set a single price, at which all orders are being executed. The trading process is a sequence of auctions based on requests to buy or sell a specified number of securities at the market price. These models do not allow to characterize the bid-ask spread, but focus on the effects of order placement by informed and uniformed traders on prices. The pivotal work in this approach is that of Kyle (1985).

The three classical papers that mathematically formalised sequential trade models are those by Copeland and Galai (1983), Glosten and Milgrom

(1985) and Easley and O'Hara (1987).

Copeland and Galai (1983) construct a one period model, where market makers pricing, given that some fraction of traders have superior information on the assets true value. The market maker is risk neutral and sets quotes to maximize his expected profit. Uninformed traders know how the general pricing process works, but they do not know the true value of the asset. The market maker cannot identify informed traders, however he knows the probability that any trade comes from an informed or from an uninformed trader. Therefore, the quotes set by the market maker emerge from a profit maximization problem, because he calculates the expected profit from any trade, taking into account the probabilities of losing to the informed and gaining to uninformed. The weakness of this model is that all private information is made public after a trade is conducted. Even when repeated rounds of trading are allowed, the expected loss of the market maker will remain the same, so he has no incentive to change his quotes. This means, that in this framework, the trading process is not informative at all. However, if private information is revealed after each round, sequences of buys and sells may reveal the underlying information process and affect the behaviour of prices.

The learning process from the order flow has been analysed in a dynamic framework by Glosten and Milgrom (1985) and Easley and O'Hara (1987). Informed traders will reveal their information by selling the asset, if they know *bad news* and buying it if they observe *good news*.Therefore, the fact that someone wants to sell may be interpreted as a signal to the market maker that bad news have been received by this trader, but it may also mean, that the trader is uninformed and simply need liquidity.

Easley and O'Hara (1987) introduced the notion of *information uncertainty.* Glosten and Milgrom (1985) assumed that, even if the market maker does not observe the information event, he knows that there are traders who always know either good or bad news. In this work, instead, it is introduced a third possibility, i.e. the absence of any private information. In this case the market maker will receive orders only from uninformed traders.

Another difference with the two previous works, is that the assumption that a fixed number of securities is traded is relaxed. Now the market maker can learn both from the direction and the size of trades. In Easley and O'Hara (1987) may be traded two different trade sizes, *large* and *small* quantities. It is assumed that uninformed traders will transact both quantities, otherwise trade size will identify the type of trader unambiguously.

Both types of models have their deficiencies and their merits. However, the sequential trade model is more corresponding to the actual features of the government bond markets and, in particular, to the data available for the empirical analysis. All these aspects make us prefer a sequential trade approach to a batch approach. It represents not only a theoretical model of the effects of information asymmetries on price setting behaviour, but it also provides a coherent framework that can be used to estimate structural parameters of the model form observable quantities that are typically contained in high frequency transactions data sets from financial markets.

2.1 Sequential trade models under asymmetric information

In this section we will briefly review some of the sequential trade models that have been used to analyse securities behaviour under asymmetric information. We will use the model used in Easley et al. (1996b) as the basic sequential trade model, since it may be considered a simplified version of its predecessors Easley and O'Hara (1987) and Easley and O'Hara (1992). Other models may be viewed as a generalization of this, so it will serve as a basic framework for more complex models.

Easley et al. (1996b) setup a mixed discrete and continuous time sequential trade model of the trading process. In this framework traders arise because of the interactions of three types of economic agents: informed and uninformed traders and a risk-neutral, competitive market-maker. The arrival rates of informed and uninformed traders are governed by independent Poisson process and the likelihood of the occurrence of three different types of information events (no news, good news and bad news) which are chosen by nature every day, before the first trade take place. In this model, the difference between bid and ask quotes arises only because of asymmetric information of market participants about the occurrence of information events. Other components of the spread, such as those caused by maintaining large inventory imbalance, or by the exercise of market power by a monopolist market maker are left aside.

Other models, add to the basic sequential trade model in Easley et al. (1996b) trade size and time effects. Theoretical foundations for the inclusion of these aspects have been developed in Easley and O'Hara (1987) and Easley and O'Hara (1992). In these works the trading day is divided into discrete time intervals, where each interval is long enough to accommodate just one trade. This assumption allows to define a third event, no-trade event, in addition to buys and sells.

In Easley et al. (1996b) no-trade intervals may arise in the course of the trading day but they are treated implicitly as zero observations of the buy and sell sequences. Throughout the introduction of the no-trade events, the duration between trades will have an effect on the market maker pricing behaviour, because long durations between trades indicate the absence of any type of information. This provide an incentive to the market maker to lower the spread, when the intensity of trading is low. In this catheogory lies the works of Easley et al. (1997a), Easley et al. (1997b).

Easley et al. (1997a) additionally distinguish between two different trade sizes, small and large trades. Easley et al. (1997b) introduce also the possibility that uninformed traders condition their trades on the observed order flow, thus inducing serial correlation in the observed trading process. They argue that uninformed traders will consider the trading history when placing their orders.

Finally, a further extension of the basic sequential trade model is to take in consideration parallel trading of a same asset in two different market designs. In this framework lies the works of Easley et al. (1996a), Easley et al. (1998) and Grammig et al. (2001). The first work analyses the possibility that the practice of cream-skimming arises in trading in two regional markets[1].

Easley et al. (1998) derive a model for parallel trading in stock and option markets. They investigate whether derivatives markets are used only for risk hedging purposes, or whether they also constitute a venue for informed traders.

Grammig et al. (2001) construct a sequential trade model, that allows for parallel trading on a floor trading system requiring physical presence of all traders and a screen trading system, that enables traders to remain anonymous.

Following Kokot (2004), a summary of frameworks and principal results of all the above models is reported in Table 1.

[1]Cream-skimming is the practice on the base of which, restricting the types of orders they will accept, some trading venues may try to attract only profitable liquidity traders, leaving larger, potentially more information based orders to other venues.

Table 1: Summary of empirical research using sequential trade models

Authors	Model	Estimation method	Principal results
Easley et al. (1996b)	Basic sequential trade model	Maximum likelihood estimation based on two trading events, for 90 stocks traded on the NYSE for 60 trading days	Probability of informed trading and bid-ask spread is generally low for high volume stocks and the same for medium and low volume stocks.
Easley et al. (1997b)	Sequential trade model with explicit consideration of no-trade intervals and trade size effects	Maximum likelihood estimation based on three (model without trade size effects) and five (model with trade size effects) trading events, for one stock traded on the NYSE (Ashland Oil) for 60 trading days.	Comparing the estimates for the sequential trade model with and without trade size effects, there is no evidence in favour of the model with trade size effects. The trade size appear to be uninformative.
Easley et al. (1997a)	Sequential trade model with explicit consideration of no-trade intervals, trade size and history dependence of the behaviour of uninformed traders.	Maximum likelihood estimation based on five different trading events (assuming that the transition probabilities between different trading events follow first order Markov chain, for 6 stocks traded on the NYSE for 60 trading days	No-trade intervals appear to be informative in all cases. Trade size is informative when history dependence of uninformed behaviour is allowed for.
Brown et al. (1999)	Sequential trade model with explicit consideration of no-trade intervals, trade size effects and limit order submission.	Maximum likelihood estimation based on nine different trading events, for 6 stocks traded on ASX for a period of 250 trading days.	Informed traders choose small volume orders more often than uninformed. There are no difference between informed and uninformed traders with respect to submission of market and limit orders.

ASX = Australian stock exchange, BODB = Berkley options database, CBOE = Chicago board options exchange, CSE= Cincinnati stock exchange,FSE = Frankfurt stock exchange,IBIS = Integrated trading and information system, NYSE = New York stock exchange.

Summary of empirical research using sequential trade models (cont.)

Authors	Model	Estimation method	Principal results
Easley et al. (2001)	Sequential trade model with explicit consideration of limit order submission by uninformed traders.	Maximum likelihood estimation based on four trading events, for 72 stocks traded on the NYSE that had a 2 to 1 stock split in 1995. The sample period spans 45 trading days before and after the eliminated period (all trades that occurred in the period beginning 20 days before and ending 20 days after the stock split were eliminated).	Informed and uninformed trading activity increases after the stock split, while probability of informed trading decrease very slightly. The execution rate of limit orders increase after the split.
Easley et al. (1996a)	Sequential trade model with explicit consideration of parallel trading on two regional markets	Maximum likelihood estimation based on four trading events, for the 30 most actively traded stocks on both the NYSE and the CSE for 60 trading days	Probability of informed trading is larger on the NYSE than on CSE.
Easley et al. (1998)	Sequential trade model with explicit consideration of dual trading on stock and option markets.	Indirect test of sequential trade model implications based on time series regressions and Granger causality test, for 50 stocks traded on the NYSE and options traded on BODB and CBOE for a period of 44 trading days.	Options volumes have predictive power for stock price changes. Informed traders trade on both, option and stock markets.
Grammig et al. (2001)	Sequential trade model with explicit consideration of parallel trading in floor and electronic markets.	Maximum likelihood estimation based on four different trading events, for 30 stocks traded on the IBIS and FSE for a period of 44 trading days.	Probability of informed trading and bid-ask spread are higher on the IBIS than on the FSE.

ASX = Australian stock exchange, BODB = Berkley options database, CBOE = Chicago board options exchange, CSE= Cincinnati stock exchange,FSE = Frankfurt stock exchange,IBIS = Integrated trading and information system, NYSE = New York stock exchange.

2.2 Models which analyse the bond market

In spite of the importance of this market, there are not many models who analyse the bond market. Dunne et al. (2007) consider the interaction between the inter-dealer (B2B) and the dealer-to-customer (B2C) segments of the European bond market. They develop a model to understand the quote dynamics in both segments and their interrelationship. They theorize that dealers are willing to hold short or long inventory positions within defined limits. Dealers are rewarded for this by arbitrage opportunities between the B2C and the B2B spreads. Dunne et al. (2007) find that a large share of the retail quotes and an even larger share of retail transactions occur within the B2B spread. Their model explain the relatively high inter-dealer spreads with the higher adverse selection risk carried by quote submission in the inter-dealer market. However, this model has some weakness. Firstly, the theoretical framework implies a rich set of predictions about the quote dynamics, but testing these predictions requires dealer specific inventory information, which is not available. Secondly, this model lies on the inventory cost, but one of the characteristics of the bond market is the possibility of hedging, that is in contrast with this assumption.

He et al. (2006) analyse the US government bond market. They use a sequential trade model to compute the probability of information-based trading . However, this model does not completely correspond to the market design of sequential trade models, since they refer to a decentralized market where each participant can post his own quotes and observe only a fraction of the buys and sells.

Finally, Arciero (2006) uses a sequential trade model to analyse an electronic centralized market where only market makers can post bid-ask quotes and can see the entire sequences of buys and sells. However, he analyses only the inter-dealer segment of the bond market.

3 Institutional environment

For this research we take into consideration two electronic secondary bond market platforms. One is MTS, acronym of Mercato Telematico dei Titoli di Stato, that is a wholesale screen-based inter-dealer market for government securities. As an inter-dealer platform, individual customers are not admitted, instead only dealers are allowed to participate (i.e. banks and financial institutions and other professional intermediaries who buy and sell securities for their own account and on behalf of their customers).

The other one is BondVision, part of the MTS Group, it is a wholesale screen-based multi-dealer-to-customer electronic market for fixed income securities[2]. On BondVision, primary dealers trade directly with institutional investors (insurance and asset management companies) by means of a multiple price auction system.

3.1 MTS

The original MTS market was first introduced in Italy in 1988, it was the first electronic market created in order to enhance trading in the secondary market of Italian government bonds. MTS has been the object of many changes during the past years, starting with the diversification of securities traded that now include, apart from the government bonds, also other fixed income securities, that already had a market, also with considerable proportions, but as an over-the-counter one. During the last two decades, the MTS platform has been typified by many changes, the most important in chronological orders were: the reform in 1994, the privatization into MTS

[2] According to the Bank of Italy classification. www.bancaditalia.it/sispaga/sms/mmf/mtsbond.

S.p.A. which took place in 1997 and the full anonymity of traders in 2003. Table 2 gives a clearer picture of the changes which have taken place during the last twenty years.

Table 2:
Changes in the Italian secondary bond market 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 counterpart (CCP) system

Source: Scalia and Vacca (1999) and Girardi and Piga (2007).

According to the MTS website, MTS S.p.A. is a regulated market,it provides wholesale electronic trading of Italian government bonds and other types of fixed income securities. It is regulated by the Italian Ministry of Economy and Finance, Bank of Italy and CONSOB. The majority stake is held by Borsa Italiana (60.37 per cent), instead the remaining shares are owned by international financial institutions[3].

In 1999, with the introduction of Euro as the single European currency,

[3] An exhaustive list of these financial institutions is available on the MTS website, under the heading "shareholders institutions". www.mtsspa.it/index.php.

EuroMTS was created. It is a private London-based company that manages the pan-European electronic trading platform for government and quasi-government bonds denominated in Euro with at least € 5 billion outstanding. Today EuroMTS is completely owned by MTS S.p.A.

In May 2001 was launched the EuroCredit MTS, a division of EuroMTS, which operates as an electronic trading platform for high-quality covered bonds. There are MTS Domestic Markets which list the government bonds of the respective European country[4].

The latest addition to the "MTS world" is the NewEuroMTS which is a market built for the trading of euro-denominate government securities of the ten new States entered in the European Union on 1 May 2004[5].

The Italian MTS is divided into two sections: one for spot trading where bonds are exchanged for cash (MTS Cash) and the other is a market for repurchased agreements (MTS Repos), in which who sells or buys commits himself respectively to buy or sell the same security back at a future date for a specified price[6].

On MTS Cash segment there are two types of market participants. Participants are qualified as dealers and primary dealers. Primary dealers act as market makers, continuously quoting two-way proposals (bid and ask prices) that are valid for all participants and for the whole day, unless they are not modified, cancelled, automatically matched or hit by incoming orders. Market takers have not any market making obligation, they must simply accept or not the quotes of market makers. Since primary dealers, unlike dealers,

[4] MTS has been successfully launched also outside the Euro area, e.g. MTS Japan Ltd. and MTS Israel in 2006.

[5] Countries whose bonds are eligible for trading in the NewEuroMTS Market include: Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia. www.mtsspa.it/index.php.

[6] If we want to take into consideration also the "grey market", where government bonds not yet issued can be traded, actually the segments are three.

may also formulate proposals on any other tradable product and issue orders for proposals made by other market participants, they can act both as price makers and price takers[7].

Within the group of primary dealers, for purposes of public debt management, the Ministry of the Economy and Finance selects a restricted list of so-called Specialists who have to satisfy more stringent requirements. A number of different short-term and long-term government bonds are traded on the Italian MTS platform: floating rate treasury certificate (CCTs), fixed rate bonds (BTPs), inflation-linked bonds (BTPis) and zero-coupon securities (BOTs and CTZs). There are precise rules governing the functioning of MTS. There are some market making obligations, involving quoting a minimum quantity of a certain bond[8], within a maximum spread (which varies according to the maturity of the asset; it is higher for assets with a longer maturity) for a minimum cumulative amount of time of at least five hours per day. Finally when they post quotes they must also specify if it is a *block* or a *drip* quantity. The former represents the overall size of the proposal, the latter the part of the order that is made visible to the market. The MTS system actually works as a limit order book, any bond is assigned to many primary dealers. The trading platform provides a lot of real-time screen-based information to all market participants, who can easily know the state of the market and observe the order flow.

The "live" market pages are:

1. The *quote page* which gives the market makers the possibility to insert offers; posted proposals can be modified, suspended or reactivated.

[7]While this work is being carried out there are 29 primary dealers and 71 dealers, operating on the Cash segment.

[8]Proposals must be formulated for a minimum lot of 2,5 or 5 million of Euro according to the instrument traded. Participant may trade the minimum quantity or its multiple. www.mtsspa.it/index.php.

2. The *market depth page* allows participants to see the best 5 bid and ask prices for each security chosen together with its aggregated quantity.

3. The *best page* shows the best bid-ask spreads together with its aggregate quantity for all products.

4. The *super best page* shows the best price for bonds listed on both the domestic MTS and the EuroMTS. Market maker who has access to both markets can choose parallel quotation, i.e. they can simultaneously post proposals on both platforms.

5. The *live market page* shows for every bond the average weighted price and the cumulative amount being traded so far.

Other rules concern trading time. The MTS market is divided into four phases: *pre-market* time (from 7:30 am to 8:00 am CET), during this stage only market makers are fully operative, they can issue and change their proposals, but primary dealers can see only their own proposals.

The *preliminary market* time (from 8:00 to 8:15 am CET) during which both primary dealers and dealers are active. However, during this phase, it is not allowed the automatic matching among proposals. This is a useful period because market makers have the opportunity to adjust their proposal on the base of the other's market makers observed prices.

The *open market* time (from 8:15 am to 5: 30 pm CET) during which it is possible to send proposals and trade and also the automatic matching is made available.

Finally the *close market* time during which no trading is allowed but only the settlement of the contracts already concluded.

Anonymity prevents dealers form managing the counterpart risk, furthermore, in order to mitigate this risk, traders can rely on a central counterpart service. Since the end of 2002 a central counterpart service has been active on an optional basis, supplied by Cassa di Compensazione e Garanzia of Italy and LCH. Clearnet of France. The role of the central counterpart is to interpose itself between the parties involved in the trades, becoming the buyer to the seller and the seller to the buyer in order to guarantee the execution of the trades by relying on the margin that the trades must deposit. Thus, anonymity is guaranteed at least until the execution of trades, when the identity of the parties could be revealed unless there is the use of the central counterpart, in which case, anonymity is guaranteed also after the execution of trades.

3.2 BondVision

BondVision is a multi-dealer-to-customer electronic bond trading market. It is another regulated market, supervised by the Italian Ministry of Economy and Finance for the government bonds and by CONSOB for the non-government trading section. It was launched in 2001 in response to continuous requests from institutional investors for access to the liquidity of the MTS markets.

BondVision allows participants, qualified as primary dealers, to trade directly with clients, qualified as institutional investors, such as investment managers, hedge funds, private banks (for this reason we classify BondVision as another wholesale market, according to the definition on the Bank of Italy, rather than as a retail market, as defined in some papers[9].

On MTS, primary dealers insert a proposal on the Best Page and all the market participants hit the bid or ask price depending on whether they want to sell or buy. Subsequently the contract is finalised, i.e. the "‘click and

[9] See Dunne et al. (2007)

trade" system, and finally settlement instructions are automatically generated.

On BondVision platform, instead, a contract is generated only as a consequence of a request from a client (end-user). Three phases characterize the process on BondVision platform: request, proposal and acceptance.

During the request phase, clients can select a product, the direction of their trade (if they want buy or sell) and the amount of their title and via the Request for Quote (RFQ) or request for switch quote (RFSWQ) functionalities, simultaneously send an electronic trade request to a maximum number of dealers, hence starting an auction[10].

During the proposal phase, each dealer participating in the auction send a responding bid or offer allowing the client to execute the trade at the best price. Dealers are not required to provide quotes when requested and clients are not obliged to accept any of the quotes they receive. They have 90 seconds to decide. Also on BondVision there is a Best Page, however the prices are indicative and not executable and it is absolutely not necessary that the requests are present in a list on the Best Page, so there is not a proper order book as for MTS. Furthermore, on BondVision, the client can also ask for a different settlement time. On BondVision there exists a minimum request obligation, the minimum lot is €100.000[11]. We have to point it out that BondVision is not an anonymous environment, since, when a client send a RFQ, he selects the dealers and the dealers selected, in turn, know who is the client who sent them the request. Furthermore, when a

[10]Each client is not allowed to send a RFQ to every dealer, but he can request quotes only to a certain number of dealers (At the moment five). More precisely, when a new client joins BondVision, he gives preference to some dealers and each dealer selected, in turn, agrees to trade with the client and chooses the titles on which is willing to offer liquidity.

[11]The Bank of Italy is currently revising the regulation, in order to diminish the minimum tradable quantity to 1.000.

dealer sends a proposal to answer a request of a client, he knows the prices that other dealers involved have quoted but he does not know their identities.

During the last phase, the contracts concluded are regulated directly by the parts. There is any regulation for the settlement. Thus, since there is any regulation for the settlement procedure, of course there is no possibility to make use of the central counterpart, so there is not anonymity neither in this phase.

4 The model

4.1 The information and trading structure

Our model belongs to the class of "sequential trade models" that date back to the work of Glosten and Milgrom (1985). More precisely it lies in the category of those works which use a model *á la* Easley and O'Hara (1992). These types of models introduce as a difference to the classic sequential trade model an additional source of uncertainty, that they define event uncertainty which arises because an information event could have occurred or not.

We modify this reference model with adjustments that partly reflect those made by other works and partly are changes introduced for our specific duty.

We consider an asset which has been contemporaneously traded on both an inter-dealer and a dealer-to-customer platform, which are differing in many respects. The true value of the asset is represented by a random variable V. On the inter-dealer platform there are many market makers who act competitively and continuously post bid and ask prices at which a trade can take place.

Following the hypothesis of Glosten and Milgrom (1985) model, market makers are assumed to be rational, risk-neutral and acting competitively. In their model there is the presence of a single market maker (in our case there are many market makers, but since they are assumed to act competitively, the hypothesis can be considered still valid).

The rationality hypothesis implies that the market maker knows that the order flow (i.e. the sequence of buys and sells occurred throughout the day) is correlated with the true value of the asset, so he uses the indirect evidence from the order flow to infer what this underlying value could be. The market maker can learn from the order flow. Each time that he observes a buy, he can infer that this trade comes either from an informed trader, who has positive private information concerning the traded asset, or from an uninformed one. On the contrary, if he observes a sell he can assume that the order comes from an informed trader who knows bad news, or from an uninformed one.

The key to extract information from the order flow is a Bayesian learning process, throughout which the market maker reviews his beliefs about the bid-ask quotes observing the sequences of buys and sells. Competition dictates that any rent earned on trades would be put away by a competing specialist. The market maker sets the bid-ask spread in order to have zero expected profit and avoid entries. Competition drives profit to zero.

The risk neutrality assumption avoids that inventory matters, as it would instead be the case with risk aversion or if the order flow were not observable to all market makers. In this case, the market maker's prices might reflect information known only to himself, but with risk-neutrality such inventory-based pricing effects will not arise.

The dealer-to-customer platform, is instead a quote-driven market where clients send requests for quotes to dealers who are mainly those who act as market makers on the inter-dealer platform. Thus, it is clear that the two platforms differ widely for many aspects, but the difference that is more concerned with our purpose is the dissimilar degree of transparency which characterizes them, given that we are interested in investigating the presence of asymmetric information in the treasury bond markets and empirically inspecting if informed traders prefer the less transparent one. The trading period is a trading day, trading days are indexed by $i \in [1, I]$. Each trading day is divided into trading intervals of a given length, time within the trading day is discrete and it is indexed by $t \in [0, T]$ and at each interval a trader is selected. The length of the trading interval is chosen to make possible at least one trade in each interval. The choice of a trading day as trading period is certainly arbitrary and not so respondent to reality, because prices could adjust to new information in minutes and new information events could happen more frequently than once per day. However, since the trading period is defined as the average time it takes to incorporate private information into prices, the choice of the trading day as trading period seems plausible. Moreover, Easley and O'Hara (1992) uphold the choice of a trading day as trading period because, using their words,*"[...]what matters for our analysis is the learning confronting market participants. This is most easily characterised by adopting the fiction of a trading day and assuming that information events occur only between trading days"*[12].

Each trading day, before trading begins, nature selects whether or not an information event will occur. Information events are assumed to be independently distributed [13].

If an information event has occurred, this means that there has been the delivery of a signal (Ψ) about the true value (V) of the asset; this happens with probability α. When an information event has occurred, the type of

[12] Easley and O'Hara (1992), p. 580.

[13] Arciero (2006) does not find a univocal solution to the rejection or not of this assumption, since the result of the specification test is not clear.

signal can be a high signal (H) in case of good news (g), with probability δ, or a low signal (L) in case of bad news (b), with probability $(1-\delta)$.

On the contrary, when no private information is disclosed, we will have a no-event day, in which case the signal is $\Psi = 0$, with probability $(1-\alpha)$. If there is no event, the probability of a trade is given respectively by ϵ_Q and ϵ_O for the quote-driven and the order-driven platforms and, similarly, that of a no trade by $(1-\epsilon_Q)$ and $(1-\epsilon_O)$ always for the two platforms.

Let $(V_i)_{i=1}^{I}$ be the random variable giving the value of the asset at the end of each trading day. During day i, if an information event occurs, the value of the asset conditional on good news is $\overline{V}_i = E[V|\Psi = H]$, on bad news is $\underline{V}_i = E[V|\Psi = L]$.
The value of the asset if no news occurs is $V_i^* = \delta \underline{V}_i + (1-\delta)\overline{V_i}$, (assuming, of course, $\underline{V}_i < V_i^* < \overline{V}_i$).

What we have been describing so far represents what Easley et al. (1997a,b) called the *information process* which describes the information state that is reached only at the beginning of each trading day. Here after, there is the beginning of what could be defined as the *choosing process*, which illustrates the choice of the platform from the market maker, which is not necessarily a mutually exclusive choice, since the market maker can take a different position contemporaneously on both platforms.

In our model market makers decide on which platform to trade, they choose to trade on the inter-dealer quote-driven platform with probability β and on the dealer-to-customer order-driven platform with probability $(1-\beta)$.

The last stage is, using again the words of Easley et al. (1997a,b), the *trading process* which describes the traders' choices and their behaviour during each information state. For the trade in the next trading interval, only the last two processes are repeated and this continues through the trading day.

At each trading interval a trader is selected. If an information event has occurred, an informed trader is selected with probability μ_Q on the quote-driven platform and μ_O on the order-driven platform and then he can choose whether to buy or sell with respective probabilities.

Informed traders know, before the trading day begins, whether the true value of the asset will take a high or low value.

At each trading interval an informed trader will buy the asset if nature has delivered good news, with probability one, and he will sell it, with probability one, if the nature has delivered bad news.

Similarly, an uninformed trader is selected with probability $(1 - \mu_Q)$ (quote-driven platform) and $(1 - \mu_O)$(order-driven platform), and again he decides to buy, sell or not to trade with the respective probabilities.

If no information event has occurred, all traders are uninformed and the trader selected may choose again to sell, buy or not to trade. Thus, an informed trader will always trade provided that the ask price is below the value of the asset in case of a high signal or the bid price is above the value of the asset in case of a low signal.

An uninformed trader, instead, will trade only on the base of his portfolio purposes.

The market maker knows that there are informed and uninformed traders in the market, but he does not know with which type of trader is actually trading. Furthermore, we assume that the arrival rates of uninformed and informed traders in both markets is given, however, there is no reason to think that these arrival rates must be equal between the two markets.

The addition to the market structure of the event uncertainty at the beginning of each trading day, with respect to the Glosten and Milgrom

(1985) model, implies that in some time intervals there could be no trade. In this perspective, market makers learn not only from trades but also from the lack of trades because each event provides an information.

Since informed traders are assumed always to trade if selected, all the no trading intervals happen because an uninformed trader was selected and he has decided not to trade.

Given these assumptions, we might expect that the probability of a no trading interval occurring is negatively correlated with the probability of a newsworthy event, Brown et al. (1999) reach the same conclusions, using only order data, so they consider, instead of no trading intervals the no order intervals.

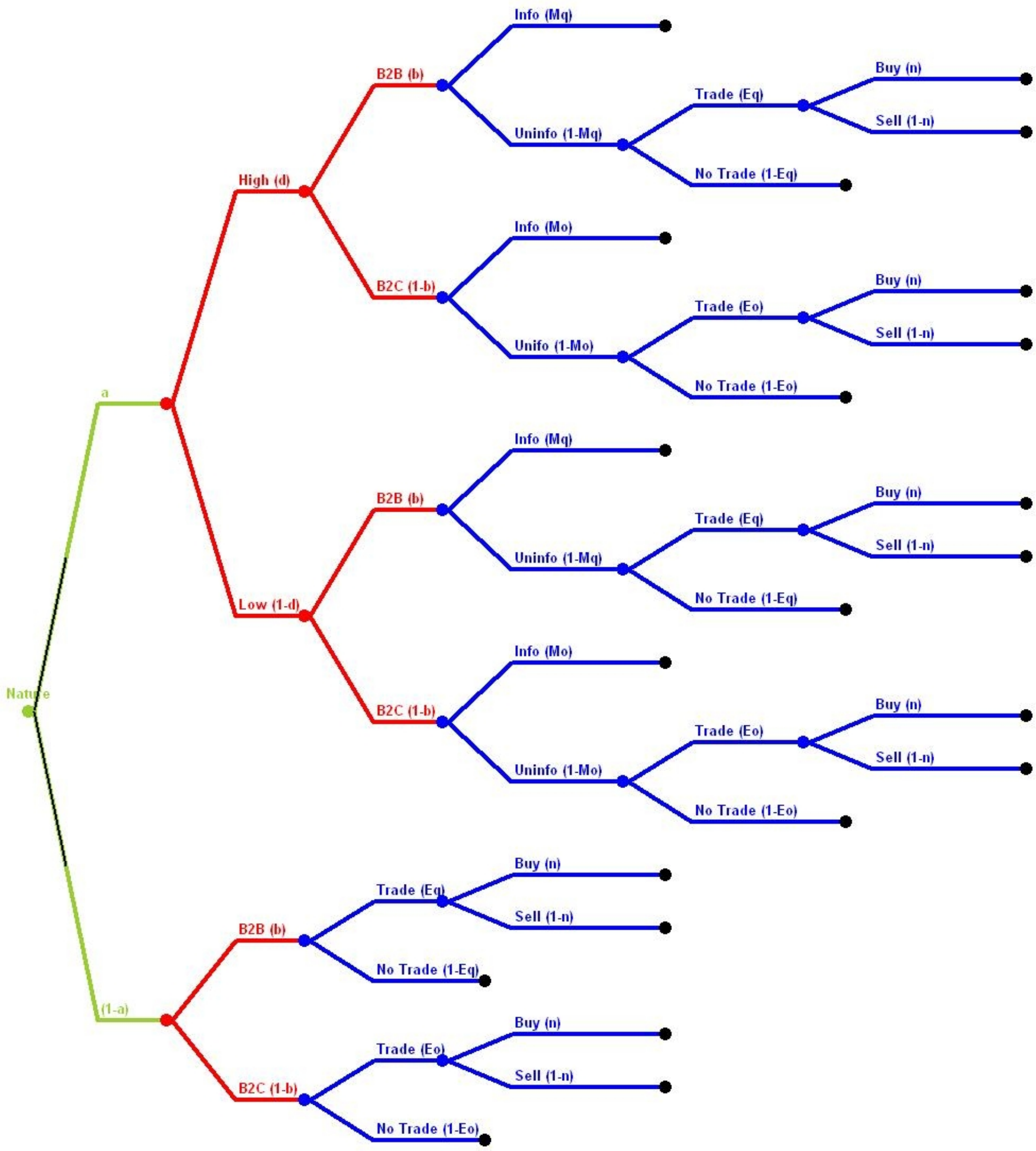
However, we have to bear in mind that a no-trade observation is not a sufficient component by itself to infer whether there has been an information event. In fact, this can occur both when there has not been any information event and when a trader decides not to trade for portfolio reasons. At the same time, we have to notice that a no-trade outcome is more likely to occur when there is no new information; this statement can be confirmed simply looking at the probabilities. Consider, as an example, only the quote-driven market. If there is no new information event, the probability of no trade is given by $(1 - \epsilon_Q)$, instead if an information event has occurred and the uninformed trader has decided to not trade, this probability falls to $(1 - \mu_Q)(1 - \epsilon_Q)$, because now there are both informed and uninformed traders in the market.

For our model, we are considering the parallel trading of a same asset on two trading platforms of the secondary government bond market. In constructing our model we extend the model of Easley and O'Hara (1992) and we follow also the work of Grammig et al. (2001) who analyse the parallel trading in the German stock market, where an anonymous electronic market and a non-anonymous trading system coexist.

In the afore mentioned work, the authors wonder about the coexistence of markets with differing degrees of anonymity and wondered which traders prefer which market. They test empirically the hypothesis that informed traders prefer the anonymous market.

In our specif case, we want to investigate the presence of informed and uninformed traders on both platforms and we want to verify the assumption that the presence of informed traders is grater on the market characterised by a higher degree of transparency. On both markets there is the presence of informed and uninformed traders. Informed traders buy on the two platforms with probability one if they know good knows and zero if they know bad news; uninformed traders instead, after having decided to trade, can choose if buy with a probability η or sell with probability $(1 - \eta)$. The overall decisional process is shown in the tree diagram in Figure 1.

Figure 1: Tree diagram of the trading process



The evolution of prices through the day follows a Bayesian learning process[14]. The market maker does not know neither if an information event has occurred nor if it is a good or a bad event. However, the market maker can observe all trading activity, this allows him to capture information and to revise his beliefs. This revision, in turn, causes quotes and prices to adjust.

Consider the market maker acting on the inter-dealers quote-driven platform[15]. At the beginning, when market opens, the market maker beliefs about the unconditional probabilities for no news (n), good news (g) and bad news (b) are given by: $P_Q(0) = (1-\alpha, \alpha\delta, \alpha(1-\delta)$. After each trade interval, these probabilities are updated, using Bayes' rule.
$P_Q(t) = (P_{Q,n}(t), P_{Q,g}(t), P_{Q,b}(t))$ is the vector of the subjective probabilities conditional on the trade history in the market prior to time t.
The expected asset value, conditional of the trade history is:

$$E_Q(V_i|t) = P_{Q,n}(t) \cdot V_i^* + P_{Q,g}(t) \cdot \overline{V}_i + P_{Q,b}(t) \cdot \underline{V}_i \tag{1}$$

The trade outcome at time t is given by:
$\theta_t \in \{NT, S_Q, S_O, B_Q, B_O\}$
where NT denotes no-trade, S_Q and S_O denote a sell respectively on the quote-driven and on the order-driven platforms, finally B_Q and B_O the same for a buy.
The first bid and ask quotes, given respectively by $b_{Q,1}$ and $a_{Q,1}$, conditional of observing a buy $B_{Q,1}$ or a sell$S_{Q,1}$ are given by:

[14]The Bayesian approach provides a mathematical rule explaining how the existing beliefs about something can be changed in the light of new evidence. Bayes rule allows to infer on the occurrence of a probabilistic event, given the observation of some data and a prior belief about the event. The generic Bayes rule can be stated as following:
$p(event|data) = \frac{(p(event)\cdot(data|event))}{p(data)} = \frac{(p(event)\cdot(data|event))}{(p(data|event)\cdot(event)+p(data|notevent)\cdot(notevent))}$
For a more detailed explanation seeO'Hara (1997), pp. 78-82.

[15]The derivation for the dealer-to customer order-driven platform is identical.

$$a_{Q,1} = E[V|B_{Q,1}] = \underline{V} \cdot P\{\Psi = L|B_{Q,1}\} + \overline{V} \cdot P\{\Psi = H|B_{Q,1}\} + V^* \cdot P\{\Psi = 0|B_{Q,1}\} \quad (2)$$

$$b_{Q,1} = E[V|S_{Q,1}] = \underline{V} \cdot P\{\Psi = L|S_{Q,1}\} + \overline{V} \cdot P\{\Psi = H|S_{Q,1}\} + V^* \cdot P\{\Psi = 0|S_{Q,1}\} \quad (3)$$

The spread is just the difference between the ask and the bid prices. In order to derive the spread, the market maker must compute the posterior probabilities applying the Bayes rule. Market makers know the structure of the market but they do not know neither if an information event is occurred and whether it is good or bad signal since it has happened, nor whether any particular trader is informed. However, market makers can watch the market and adjust their beliefs on the base of the trading activity results.This revision process causes quotes and thus prices to change. This process, for the first trade of the day, requires that the market maker calculates the expected value of the asset conditioned on any possible type of trade that can occur.

Thus, in order to determine the conditional probability of the high value ($\overline{V}$), if there was not a signal, this probability remains unchanged at δ; if, instead, an information event has occurred, $P\left\{V = \overline{V}\right\}$ becomes one if the signal is high and zero if the signal is low. Consequently, the market maker's updating formula is:

$$P\left\{V = \overline{V}|\theta\right\} = 0 \cdot P\{\Psi = L|\theta\} + 1 \cdot P\{\Psi = H|\theta\} + \delta \cdot P\{\Psi = 0|\theta\} \quad (4)$$

Since the market maker use Bayesian learning to update his beliefs, the posterior probabilities can be derived applying the following generic Bayes rule:

$$P\{\Psi = X|\theta\} = \frac{P\{\Psi = X\} \cdot P\{\theta|\Psi = X\}}{P\{\Psi = L\} \cdot P\{\theta|\Psi = L\} + P\{\Psi = H\} \cdot P\{\theta|\Psi = H\} + P\{\Psi = 0\} \cdot P\{\theta|\Psi = 0\}} \quad (5)$$

The explicit probabilities can be derived from the tree diagram in Figure 1. To give an example, the market maker's updating formula in case that a high signal has occurred, given a sale on the quote-driven platform is:

$$P\left\{V = \overline{V}|S_{Q,1}\right\} = 1 \cdot P\left\{\Psi = L|S_{Q,1}\right\} + 0 \cdot P\left\{\Psi = H|S_{Q,1}\right\} + \delta \cdot P\left\{\Psi = 0|S_{Q,1}\right\} \quad (6)$$

The posterior probabilities, on the RHS of the (5)expression, can be computed by applying the Bayes rule and using the event tree diagram. The posterior probability $P\{\Psi = H|S_{Q,1}\}$ is given by the following expression:

$$\begin{aligned} P\left\{\Psi = H|S_{Q,1}\right\} &= \\ &\frac{P\{\Psi = H\} \cdot P\left\{S_{Q,1}|\Psi = H\right\}}{P\{\Psi = H\} \cdot P\left\{S_{Q,1}|\Psi = H\right\} + P\{\Psi = L\} \cdot P\left\{S_{Q,1}|\Psi = L\right\} + P\{\Psi = 0\} \cdot P\left\{S_{Q,1}|\Psi = 0\right\}} \\ &\frac{\alpha\delta\beta(1-\mu_Q)\epsilon_Q(1-\eta)}{\alpha\delta\beta(1-\mu_Q)\epsilon_Q(1-\eta) + \alpha(1-\delta)[\beta\mu_Q + \beta(1-\mu_Q)\epsilon_Q(1-\eta] + (1-\alpha)\beta\epsilon_Q(1-\eta)} \end{aligned} \quad (7)$$

It is possible to derive, in the same manner, the other posterior probabilities in order to obtain the initial bid and ask quotes set by the market maker.

$$\begin{aligned} P\left\{\Psi = L|S_{Q,1}\right\} &= \\ &\frac{P\{\Psi = L\} \cdot P\left\{S_{Q,1}|\Psi = L\right\}}{P\{\Psi = H\} \cdot P\left\{S_{Q,1}|\Psi = H\right\} + P\{\Psi = L\} \cdot P\left\{S_{Q,1}|\Psi = L\right\} + P\{\Psi = 0\} \cdot P\left\{S_{Q,1}|\Psi = 0\right\}} \\ &= \frac{\alpha(1-\delta)\left[\beta\mu_Q + \beta(1-\mu_Q)\epsilon_Q(1-\eta)\right]}{\alpha\delta\beta(1-\mu_Q)\epsilon_Q(1-\eta) + \alpha(1-\delta)[\beta\mu_Q + \beta(1-\mu_Q)\epsilon_Q(1-\eta)] + (1-\alpha)\beta\epsilon_Q(1-\eta)} \end{aligned} \quad (8)$$

$$P\left\{\Psi = L|S_{Q,1}\right\} =$$

$$\frac{P\left\{\Psi = 0\right\} \cdot P\left\{S_{Q,1}|\Psi = 0\right\}}{P\left\{\Psi = H\right\} \cdot P\left\{S_{Q,1}|\Psi = H\right\} + P\left\{\Psi = L\right\} \cdot P\left\{S_{Q,1}|\Psi = L\right\} + P\left\{\Psi = 0\right\} \cdot P\left\{S_{Q,1}|\Psi = 0\right\}}$$

$$= \frac{(1-\alpha)\,\beta\epsilon_Q\,(1-\eta)}{\alpha\delta\beta(1-\mu_Q)\epsilon_Q(1-\eta) + \alpha(1-\delta)[\beta\mu_Q + \beta(1-\mu_Q)\epsilon_Q(1-\eta)] + (1-\alpha)\beta\epsilon_Q(1-\eta)} \tag{9}$$

Reiterating the same process, it is possible to recover all the probabilities(included in the previous three expressions)and compute the first bid and ask quotes. After the first round, the market maker computes the following bid and ask quotes, now conditioned on the past history, i.e. given that the market maker has observed a buy or a sell during the first trade, and the type of trade which can take place on the second round; and so on for the subsequent trading rounds.

Assuming that a buy has occurred, on the quote-driven platform, during the first round, the prices set by the market maker will be:

$$\begin{aligned} a_{Q,2} = E\left[V|B_{Q,2}, B_{Q,1}\right] = &\\ &\underline{V} \cdot P\left\{\Psi = L|B_{Q,2}, B_{Q,1}\right\} \\ &+ \overline{V} \cdot P\left\{\Psi = H|B_{Q,2}, B_{Q,1}\right\} \\ &+ V^* \cdot P\left\{\Psi = 0|B_{Q,2}, B_{Q,1}\right\} \end{aligned} \tag{10}$$

$$\begin{aligned} b_{Q,2} = E[V|S_{Q,2}, B_{Q,1}] = &\\ &\underline{V} \cdot P\left\{\Psi = L|S_{Q,2}, B_{Q,1}\right\} \\ &+ \overline{V} \cdot P\left\{\Psi = H|S_{Q,2}, B_{Q,1}\right\} \\ &+ V^* \cdot P\left\{\Psi = 0|SQ, 2, B_{Q,1}\right\} \end{aligned} \tag{11}$$

The bid and ask prices of the second round differ from the bid ans ask prices of the first round $a_{Q,1}$ and $b_{Q,1}$ for the posterior probabilities that, for the second round, are conditioned both on the past history and on the type of trade which can occur at the current round.

$$P\left\{\Psi = H|S_{Q,1}, S_{Q,2}\right\} = \frac{P\{\Psi = H|S_{Q,1}\} \cdot P\{S_{Q,2}|\Psi = H\}}{P\{\Psi = L|S_{Q,1}\} \cdot P\{S_{Q,2}|\Psi = L\} + P\{\Psi = H|S_{Q,1}\} \cdot P\{S_{Q,2}|\Psi = H\} + P\{\Psi = 0|S_{Q,1}\} \cdot P\{S_{Q,2}|\Psi = 0\}} \tag{12}$$

Where $P\{\Psi = H|S_{Q,1}\}$, $P\{\Psi = L|S_{Q,1}\}$ and $P\{\Psi = H|S_{Q,1}\}$ are the posterior probabilities derived during the first round.
Furthermore, $P\{S_{Q,2}|\Psi = H\} = P\{S_{Q,1}|\Psi = H\}$,
$P\{S_{Q,2}|\Psi = L\} = P\{S_{Q,1}|\Psi = L\}$ and $P\{S_{Q,2}|\Psi = 0\} = P\{S_{Q,1}|\Psi = 0\}$, because the traders are assumed independently drawn from the same distribution.

This process is reiterated many times to derive the bid and ask quotes set by the market maker at each round. The bid and ask quotes at time t will be given by the expected value of the asset conditional on the past history (the number of buys,sells and no trades reported between the first and the t^{th} interval) and the type of trade which may take place at time *t-1*. For a full derivation see Appendix B.

4.2 The trading process

The empirical application of sequential trade models raises some problems due to the fact that neither the occurrence of information events nor the associated arrival of informed and uniformed traders is directly observable. What instead it is usually directly observable, is the sequence of trading events, i.e. the incoming buy and sell orders.

With a data set which contains daily records of the number of sells and buys for a total number of trading days we can estimate the nine parameters of the trade process and inference of the relevance of informed trading can be drawn employing standard maximum likelihood techniques.

The parameter vector is: $\Omega = [\alpha, \delta, \beta, \mu_O, \mu_Q, \epsilon_O, \epsilon_Q, \eta]'$. Assuming that arrival rates depend on the type of trading day, it is possible to infer information, concerning the event type and the associated arrival rates, observing the number of buys, sells and no trades on different days in the sample.

To estimate the nine parameters we write a likelihood function to describe the model and then fit this function to the trading data, using a maximum likelihood technique. Writing the likelihood function entails some steps.

First we have to estimate the joint likelihood of observing a given trade history on both markets. The probability of observing the five different events: B_O buys on the order-driven platform, B_Q buys on the quote-driven platform, S_O sells on the order-driven platform, S_Q sells on the quote-driven platform and NT no-trade events occurred in a day, conditional of the choice made by the nature (good news, bad news, no news).

Reminding that during a day, trading outcomes are independently drawn by the same distribution. Hence, the probability of observing the five different events on a good news day i is given by:

$$\begin{aligned}
&P_g\left(B_O \cap B_Q \cap S_O \cap S_Q \cap NT || \text{good news}; \Omega\right) = \\
&\quad \left[(\beta\mu_Q) + (\beta\left(1-\mu_Q\right)\epsilon_Q\eta)\right]^{BQ} \cdot \left[(1-\beta)\,\mu_O + (1-\beta)\,(1-\mu_O)\,\epsilon_O\eta\right]^{BO} \\
&\quad \cdot \left[\beta(1-\mu_Q)\epsilon_Q(1-\eta)\right]^{SQ} \cdot \left[(1-\beta)(1-\mu_O)\epsilon_O(1-\eta)\right]^{SO} \qquad (13) \\
&\quad \cdot \left[\beta(1-\mu_Q)(1-\epsilon_Q) + (1-\beta)(1-\mu_O)(1-\epsilon_O)\right]^{NT}
\end{aligned}$$

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

$$
\begin{aligned}
&P_b\left(B_O \cap B_Q \cap S_O \cap S_Q \cap NT || \text{bad news}; \Omega\right) = \\
&\quad \left[\beta\left(1-\mu_Q\right)\epsilon_Q\eta\right]^{BQ} \cdot \left[\left(1-\beta\right)\left(1-\mu_O\right)\epsilon_O\eta\right]^{BO} \\
&\quad \cdot \left[\beta\mu_Q + \beta\left(1-\mu_Q\right)\epsilon_Q\left(1-\eta\right)\right]^{SQ} \\
&\quad \cdot \left[\left(1-\beta\right)\mu_O + \left(1-\beta\right)\left(1-\mu_O\right)\epsilon_O\left(1-\eta\right)\right]^{SO} \\
&\quad \cdot \left[\beta\left(1-\mu_Q\right)\left(1-\epsilon_Q\right) + \left(1-\beta\right)\left(1-\mu_O\right)\left(1-\epsilon_O\right)\right]^{NT}
\end{aligned}
\tag{14}
$$

And finally on a no news day, the corresponding probability is the following:

$$
\begin{aligned}
&P_n\left(B_O \cap B_Q \cap S_O \cap S_Q \cap NT || \text{no news}; \Omega\right) = \\
&\quad \left[\beta\epsilon_Q\eta\right]^{BQ} \cdot \left[\left(1-\beta\right)\epsilon_O\eta\right]^{BO} \\
&\quad \cdot \left[\beta\epsilon_Q(1-\eta)\right]^{SQ} \cdot \left[(1-\beta)\epsilon_O(1-\eta)\right]^{SO} \\
&\quad \cdot \left[\beta\left(1-\epsilon_Q\right) + \left(1-\beta\right)\left(1-\epsilon_O\right)\right]^{NT}
\end{aligned}
\tag{15}
$$

Each of the three types of event has five different equations, for a total of fifteen. It is possible to recover the unconditional likelihood for a generic trading day, is a mixture of the three conditional probabilities (13),(14) and (15), weighted by the probabilities of observing the information regimes: $\alpha\delta$ for good event days, $\alpha(1-\delta)$ if bad event days take place and $(1-\alpha)$ for non event days.

Following the unconditional likelihood for a single day:

$$P_i\left(B_O \cap B_Q \cap S_O \cap S_Q \cap NT;\Omega\right) =$$

$$\begin{aligned}
&\alpha\delta \cdot P_g\left(B_O \cap B_Q \cap S_O \cap S_Q \cap NT|\text{good news};\Omega\right) + \\
&\alpha\left(1-\delta\right) \cdot P_b\left(B_O \cap B_Q \cap S_O \cap S_Q \cap NT|\text{bad news};\Omega\right) + \\
&\left(1-\alpha\right) \cdot P_n\left(B_O \cap B_Q \cap S_O \cap S_Q \cap NT|\text{no news};\Omega\right) \qquad (16)
\end{aligned}$$

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

$$L\left(\alpha,\delta,\beta,\mu_O,\mu_Q,\epsilon_O,\epsilon_Q,\eta|B_{Ot},B_{Qt},S_{Ot},S_{Qt},NT_t\right) =$$

$$= \sum_{t=i}^{I} \left\{ \begin{array}{l}
\alpha\delta \cdot P_g\left(B_O \cap B_Q \cap S_O \cap S_Q \cap NT|\text{good news};\Omega\right) + \\
\alpha\left(1-\delta\right) \cdot P_b\left(B_O \cap B_Q \cap S_O \cap S_Q \cap NT|\text{bad news};\Omega\right) + \\
\left(1-\alpha\right) \cdot P_n\left(B_O \cap B_Q \cap S_O \cap S_Q \cap NT|\text{no news};\Omega\right)
\end{array} \right. \qquad (17)$$

5 Data

Our database is composed of two datasets of fixed rate bonds (BTP - Buoni Pluriennali del Tesoro) with an original ten-year maturity,which have been on-the-run and off-the-run during the period taken into consideration.

One dataset contains records of traders and proposals of BTPs traded on MTS platform from January 2004 to November 2006. For our purpose we will focus only on the MTS Cash segment, characterized by institutional features which are closer to those typified in the theoretical model.

The other dataset contains records of traders and requests for quotes of BTPs traded on BondVision platform form January 2004 to February 2007.

We treat our database as a time series, considering only the number of contracts on both platforms[16].

The long term fixed coupon bonds accounted for 57.59 per cent of outstanding securities for government debt on 30 June 2008 and, for the time of our sample, for 59.93 per cent[17].

One of the principal advantage of our database is that it records the trade direction, i.e. whether a trade was a buyer or a seller initiated, which is an important piece of information to conduct empirical studies. The problem is that high-frequency data sets rarely include information concerning the counterparts, so empirical works had to use *ad hoc* algorithms to infer from the data the initiator of each trade. This represents a great improvement with respect to past empirical works because these techniques were not exempt from mistakes, leaving miss-classified traders that, in turn, can significantly bias the results[18].

Before proceeding with the analysis, we adopt a procedure to filter our database in order to drop biased data and errors. First of all we drop all the observations without quantities and prices.

Second, we drop all snapshots with a negative best spread, on the top of the book. [19].

Third, we eliminate all observations for the 1^{st}, 2^{nd} and 3^{rd} August 2004[20].

[16] The bonds in our database are: IT0003472336, IT0003618383, IT0003719918, IT0003844534 and IT0004019581

[17] Treasury website. www.dt.tesoro.it/en

[18] For further information see for example Ellis et al. (2000) and Kokot (2004)

[19] Best spread = best ask price - best bid price (i.e the difference between the lowest ask and the highest bid)

[20] The Financial Services Authority (FSA) found that City Group Global Markets Limited (CGML) executed a trading strategy on the European government bond markets on 2 August 2004 which involved the firm building up and then rapidly exiting from very substantial long positions in European government bonds over a period of an hour. 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 par-

For the BondVision platform, we drop all contracts for which there are no corresponding proposals or for which the time elapsed between trading and proposals is greater than 90 seconds. Since we are considering parallel trading on both platforms, we construct our investigation sample taking data form February 2004 to November 2006, for a total of 77172 observations over 708 days. The snapshots in the datasets run from 8:30am to 5:30pm[21]. Following tables show descriptive statistics of our data, for data at 5-minute intervals and for aggregate data on daily base.

ticipants from quoting on that platform. The FSA fined CGML on 28 June 2005, £13.9 million (20.9mn) for Eurobond trades. Source: www.fsa.gov.uk

[21] There are also some snapshots before 8:30am, but they are so few to be negligible.

Table 3: Descriptive statistics (5-min intervals)

Statistics	BO	BQ	SO	SQ	NT
N	77172	77172	77172	77172	77172
Mean	1.265916	.4688618	1.251899	.4427253	.5758436
Variance	1.166079	2.168952	1.48462	2.157726	.2442509
Skeweness	10.63568	10.44705	11.48178	10.63646	-.3069259
Kurtosis	157.125	206.8866	164.7231	209.6262	1.094203
Minimum	1	0	1	0	0
Median	1	0	1	0	1
Maximum	21	54	24	54	1
Mode	1	0	1	0	1

BO = Number of buys on the order-driven platform, SO = Number of sells on the order-driven platform, BQ = Number of buys on the quote-driven platform, SQ = Number of sells on the quote driven platform, NT = Number of no trade intervals.

Table 4: Descriptive statistics (trading days)

Statistics	BO	BQ	SO	SQ	NT
N	708	708	708	708	708
Mean	9.689266	51.10593	7.44774	48.25706	62.76695
Variance	55.71377	965.0849	39.06233	950.8447	155.0984
Skeweness	1.295985	1.647741	1.446309	1.4769	.2381942
Kurtosis	4.998458	7.074138	6.161667	6.091669	3.868375
Minimum	0	0	0	0	19
Median	8	44	6	41	63
Maximum	42	216	41	212	109
Mode	2	37	2	0	34

BO = Number of buys on the order-driven platform, SO = Number of sells on the order-driven platform, BQ = Number of buys on the quote-driven platform, SQ = Number of sells on the quote driven platform, NT = Number of no trade intervals.

6 Empirical analysis

We will perform a maximum likelihood estimation of our data, on the base of the log-likelihood specified in equation (17):

$$L\left(\alpha,\delta,\beta,\mu_O,\mu_Q,\epsilon_O,\epsilon_Q,\eta|B_{Ot},B_{Qt},S_{Ot},S_{Qt},NT_t\right) =$$

$$= \sum_{t=1}^{708} \left\{ \begin{array}{l} \alpha\delta\cdot P_g\left(B_O\cap B_Q\cap S_O\cap S_Q\cap NT|\text{good news};\Omega\right)+ \\ \alpha\left(1-\delta\right)\cdot P_b\left(B_O\cap B_Q\cap S_O\cap S_Q\cap NT|\text{bad news};\Omega\right)+ \\ \left(1-\alpha\right)\cdot P_n\left(B_O\cap B_Q\cap S_O\cap S_Q\cap NT|\text{no news};\Omega\right) \end{array} \right. \qquad (18)$$

First of all we have to compute the number of no trade intervals taking place between two trades. For this purpose, we construct a dummy variable (NT) for no-trading time intervals, which takes value 1 if there is not a trade and 0 otherwise.

However, the number of no trade intervals is sensitive to the length of the trading intervals, so the choice of it may have consequences. Easley and O'Hara (1992) choose 5-minute as benchmark interval because this length makes feasible at least one trade in each interval. Furthermore, we replicate our estimates using intervals of different length, to be sure that the choice of the length does not influence our results. For our study the range of possible interval lengths goes from 1 to 10 minutes, however, given the high number of observations that we already have choosing a 5-minute length interval, we replicate our analysis only for intervals longer than 5-minute.

The results of the maximum likelihood estimation (18) give the following results for the platforms:

Table 5: Parameters estimation (MTS platform)

Parameter	Coef.	Std. Err.	Z	P > |Z|	95% Conf.	Interval
α	.3804801	.0197189	19.30	0.000	.3418317	.4191285
δ	.5523178	.0318068	17.36	0.000	.4899777	.6146579
μ	.2438671	.0035026	69.62	0.000	.2370021	.2507321
ϵ	.562448	.0017519	321.06	0.000	.5590144	.5658816

Log-likelihood = -122813.62

Table 6: Parameters estimation (BondVision platform)

Parameter	Coef.	Std. Err.	Z	P > |Z|	95% Conf.	Interval
α	.3942688	0224058	17.60	0.000	.3503543	.4381833
δ	.6823738	.0314929	21.67	0.000	.6206489	.7440988
μ	.1551226	.0037176	41.73	0.000	.1478362	.162409
ϵ	.1607788	.0020581	78.12	0.000	.156745	.1648126

Log-likelihood = -36641.072

According to these results, during the sample period, market makers expect that the event days (the value of the parameter α) occur with probability 0.38 on the MTS platform and 0.39 on the BondVision platform.

Good event days (the value of the parameter δ) are slightly more likely than bad event days on MTS platform and considerably more likely on BondVision.

Market makers assign a value 0.56 to the probability that an uninformed trader execute a trade (the value of the parameter ϵ) on MTS and a value of 0.16 on BondVision.

The fraction of trades due to informed traders (the value of the parameter μ) is 0.24 on MTS and 0.16 on Bond Vision.

The estimates of all parameters are accurate, as we can infer from the confidence intervals and from the values of the standard errors. The standard errors emphasize that the accuracy of the estimates is greater for μ and ϵ than for α and δ. On the whole, the empirical evidence suggests that the maximum likelihood estimation has been successful in identifying the parameters underlying our theoretical model.

Furthermore, we derive the probability of informed trading on the two platforms assuming that the probability to encounter an informed trader on the less transparent market is higher than the corresponding probability on the more transparent one.

The probability of informed trading on the two platform is given by:

$$PIT = \frac{\alpha\mu}{\alpha\mu + (1-\mu)\,\epsilon} \tag{19}$$

giving a result of 18 per cent on MTS and of 31 per cent on BondVision. These results confirm our assumption that the probability to encounter an informed trader is higher on the less transparent platform.

We have to point out that our theoretical model is constructed for both platforms, but convergence problems have not allowed to estimate the parameters for the whole model. However, the value of the estimates that we obtain from the two separate markets are still informative.

6.1 Robustness tests

As a first test, the length of the trade intervals is varied to verify the stability of the estimates. We replicate the maximum log-likelihood for two alternative datasets, one which contains trade intervals for 8-minute length and another for 10-minute length. Arciero (2006) considers interval lengths of 1, 2, 8 and 10 minutes. He finds that the estimates of the parameter μ and ϵ exhibit an increasing path for intervals of increasing length. For our database, we do not register any difference in the estimates. A summary of the results is reported in Appendix A.

To asses the validity of the independence of information events from day to day we follow Easley and O'Hara (1992). As a first step, we need to divide the days in event and no event days. We classify event days on the base of parameter α, because event days are characterized by a higher trading volume. Our results show for a value of $\alpha = 0.38$ on MTS platform, 269 trading days and 439 no trading days. On BondVision platform, with $\alpha = 0.39$, 481 trading days and 227 no trading days are obtained.

After having divided the days in two sample we perform a run test. A run test is a non-parametric test that we use to investigate whether the sequences of event and no vent days are independent. For MTS data we obtain 277 runs of event and non event days, for BondVision we get 187 runs of event and no event days. With value of the statistic Z equal respectively to -4.6 and -10.7 we reject the null hypothesis of independence of days.

The same test is replicated for the sub-sample of event and no event days, to verify whether the arrivals of good and bad news are independently distributed. In this case we find 108 runs for MTS platform and 89 runs for BondVision. Once again we reject the null hypothesis of independence between good and bad event days.

Although this specification test reject one of the assumptions of the model, i.e. the independence of information events across the sample days, this does not mean that the theoretical model is not correct. It suggests that is necessary a further analysis, relaxing the assumption of independence and allowing the parameters of the model to be either auto-correlated or cross-correlated.

Finally, autocorrelation and partial autocorrelation of the random variables number of daily buys on MTS (B_Q), number of daily buys on BondVision (B_O), number of daily sells on MTS (S_Q), number of daily sells (S_O) on BondVision and number of no trade days (NT), show that there is persistence in the data. However, Easley and O'Hara (1992) argue that dependence does not affect the estimates of μ and ϵ, because they are determined by the number of trades and no trades occurred within a trading day. Nonetheless, the estimates of α and δ may be affected since they are derived from the distribution of trades and no trades between days. Details of the autocorrelations and partial autocorrelations for six lags are reported in Appendix C.

7 Conclusions

In this paper we investigate the presence of asymmetric information in the two secondary government bond market. We analyse the parallel trading of fixed rate bond (BTP) with a ten-year maturity on two secondary electronic platforms: the inter-dealer MTS and the dealer-to-customer BondVision.

Our model allows to explain the stochastic process governing the asset prices on the base of the number of buys, sells and no trade intervals occurred over a sample of 708 days.

Asymmetric information arises since each day nature deliver a signal to the market about the true value of the asset. This signal could be good or bad and it is delivered only to a fraction of traders (informed traders).

The dataset allows us to know exactly the type of trades occurred, i.e. if it is a buy or a sell. This is a remarkable advantage compared to works that use an *ad-hoc* algorithm to infer this piece of information, introducing noise in the results.

The two platforms under analysis differ for the degree of transparency that typifies them. We assume that the probability to encounter an informed trader on the less transparent market is higher than the corresponding probability on the more transparent one. Our results confirm this assumption, since informed traders on MTS are 18 per cent, whereas on BondVision, the less transparent platform, they are 31 per cent. Although our theoretical model is constructed to include both platforms, the value of the estimates that we obtain from the two separate markets are still informative.

Furthermore, we perform a series of robustness tests.

First we check for the robustness of our estimates to different lengths of the trade intervals. We estimate the maximum log-likelihood also for time intervals of 8 and 10 minutes, and we do not find any significant difference.

Second we perform a non-parametric run test to asses the independence of information events form day to day. This test rejects the null hypothesis of independence. However this finding does not controvert the hypothesis of our model, but calls for further analysis, in order to relax the assumption of independence and allow the parameters of the model to be either auto-correlated or cross-correlated.

Finally, we investigate the presence of autocorrelation and partial autocorrelation in the random variables of our model. Also in this case the results are not respondent to the hypothesis of no dependence, calling for further investigation.

Appendix A

Table 7: 8-min intervals (MTS platform)

Parameter	Coef.	Std. Err.	Z	P > |Z|	95% Conf.	Interval
α	.3804801	.0024091	157.94	0.000	.3757584	.3852017
δ	.5523178	.0038858	142.14	0.000	.5447017	.5599338
μ	.2438671	.0004279	569.90	0.000	.2430284	.2447058
ϵ	.562448	.000214	2627.98	0.000	.5620285	.5628675

Log-likelihood = -8228512.2

Table 8: 8-min intervals (BondVision platform)

Parameter	Coef.	Std. Err.	Z	P > |Z|	95% Conf.	Interval
α	.3942688	0027373	144.04	0.000	.3889038	.3996338
δ	.6823738	.0038475	177.36	0.000	.6748329	.6899147
μ	.1551226	.0004542	341.55	0.000	.1542325	.1560128
ϵ	.1607788	.0002514	639.44	0.000	.160286	.1612716

Log-likelihood = -2454951.8

Table 9: 10-min intervals (MTS platform)

Parameter	Coef.	Std. Err.	Z	P > |Z|	95% Conf.	Interval
α	.3804801	.0026589	143.10	0.000	.3752687	.3856914
δ	.5523178	.0042888	128.78	0.000	.5439118	.5607237
μ	.2438671	.0004723	516.25	0.000	.2429414	.2447928
ϵ	.562448	.0002362	2381.04	0.000	.561985	.562911

Log-likelihood = -6754748.9

Table 10: 10-min intervals (BondVision platform)

Parameter	Coef.	Std. Err.	Z	P > |Z|	95% Conf.	Interval
α	.3942688	.0030212	130.50	0.000	.3883474	.4001902
δ	.6823738	.0042465	160.69	0.000	.6740508	.6906968
μ	.1551226	.0005013	309.45	0.000	.1541401	.1561051
ϵ	.1607788	.0002775	579.35	0.000	.1602349	.1613227

Log-likelihood = -2015259

Appendix B

For a trade at time t we have:

$$P\left\{\Psi = H|\theta_1, \dots \theta_{t-1}, S_{Q,t}\right\} = \frac{P\left\{\Psi = H|\theta_1, \dots \theta_{t-1}\right\} \cdot P\left\{S_{Q,t}|\theta_1, \dots \theta_{t-1}, \Psi = H\right\}}{P\left\{S_{Q,t}|\theta_1, \dots \theta_{t-1}\right\}}$$

where the probability of a sale on the quote-driven platform, given $(\theta_1, \dots \theta_{t-1})$ is:

$$\begin{aligned}
&P\left\{S_{Q,t}|\theta_1, \dots \theta_{t-1}\right\} = \\
&P\left\{\Psi = H|\theta_1, \dots \theta_{t-1}\right\} \cdot \beta\left(1-\mu_Q\right)\epsilon_Q\left(1-\eta\right) \\
&+ P\left\{\Psi = L|\theta_1, \dots \theta_{t-1}\right\} \cdot \beta\mu_Q + \beta\left(1-\mu_Q\right)\epsilon_Q\left(1-\eta\right) \\
&+ P\left\{\Psi = 0|\theta_1, \dots \theta_{t-1}\right\} \cdot \beta\epsilon_Q\left(1-\eta\right)
\end{aligned}$$

The market maker's ask and bid in period t are given by expected value of the asset conditional on the history and, a buy or a sell respectively.

$$\begin{aligned}
a_{Q,t} = E\left[V|B_{Q,t}\right] = \\
&\underline{V} \cdot P\left\{\Psi = L|\theta_1, \dots \theta_{t-1}, B_{Q,t}\right\} \\
&+ \overline{V} \cdot P\left\{\Psi = H|\theta_1, \dots \theta_{t-1} B_{Q,t}\right\} \\
&+ V^* \cdot P\left\{\Psi = 0|B_{Q,t}\right\}
\end{aligned}$$

$$
\begin{aligned}
b_{Q,t} = E\left[V|S_{Q,t}\right] = & \\
& \underline{V} \cdot P\left\{\Psi = L|\theta_1, \ldots \theta_{t-1}, S_{Q,t}\right\} \\
& + \overline{V} \cdot P\left\{\Psi = H|\theta_1, \ldots \theta_{t-1} S_{Q,t}\right\} \\
& + V^{*} \cdot P\left\{\Psi = 0|s_{Q,t}\right\}
\end{aligned}
$$

Appendix C

Figure 2: Autocorrelations and partial autocorrelations of daily buys

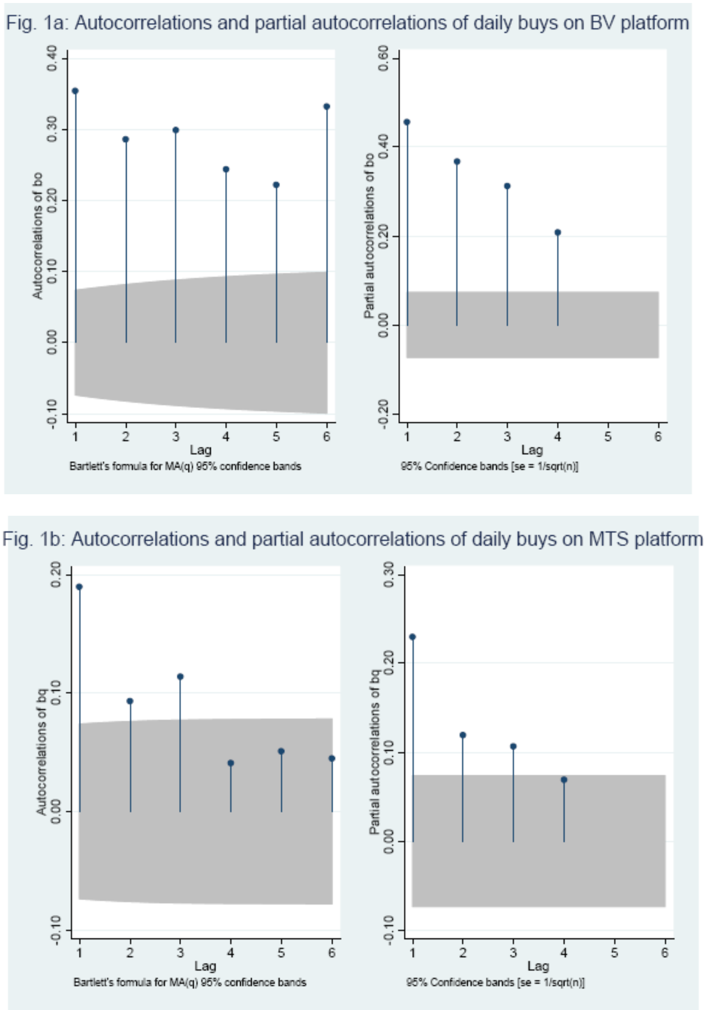


Figure 3: Autocorrelations and partial autocorrelations of daily sells

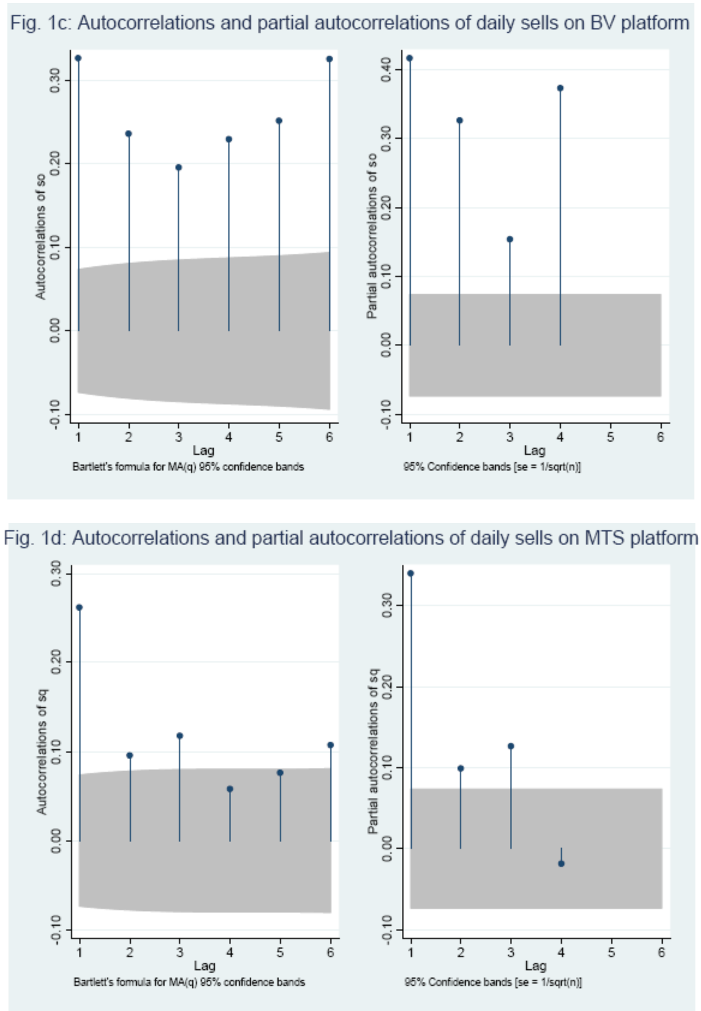
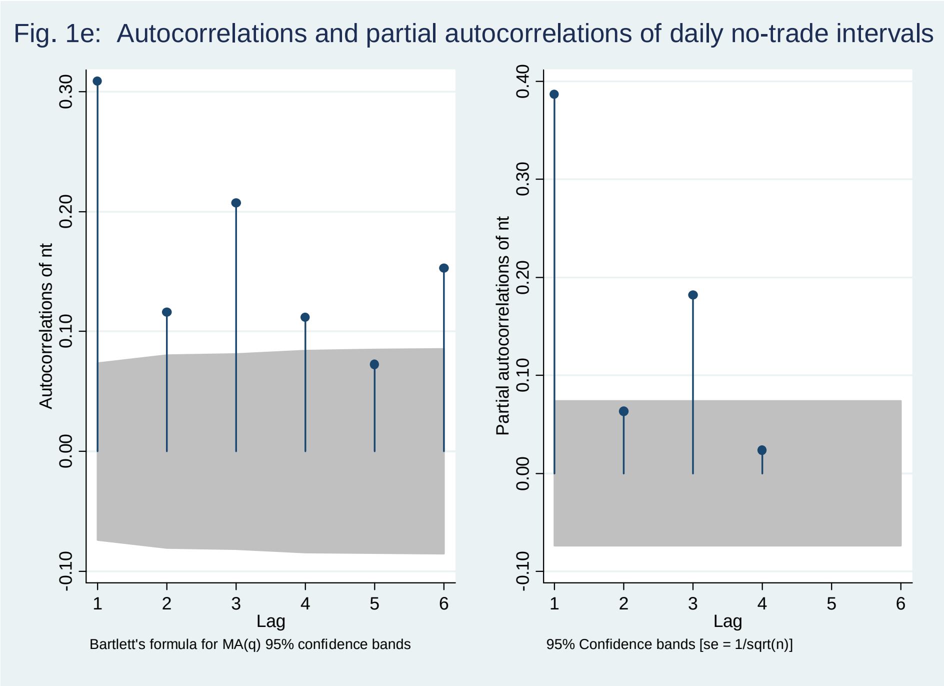


Figure 4: Autocorrelations and partial autocorrelations of daily no-trade intervals



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