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ABSTRACT

Trading European Sovereign Bonds: The Microstructure of the MTS Trading Platforms*

We study the microstructure of the MTS Global Market bond trading system. This system is the largest pan-European interdealer trading system for Eurozone government bonds. We study the volume weighted quoted spread and a variety of effective spread measures for different classes of bond maturities and issuing countries. We find that quoted and effective spreads are related to maturity and trading intensity. Estimated spreads on EuroMTS are typically slightly higher than on the domestic markets, but the difference is small in economic terms. The regression results show that order flow plays a key role in determining the price discovery in the bond market. Transitory costs are more important in markets like Italy and Belgium, which are dominated by local traders. In addition, we find a positive relationship between trading intensity and price returns, indicating findings relevant to the structure of bond markets and interdealer trading.

JEL Classification: C32 and F31
Keywords: bonds markets, microstructure and order flow

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1 Introduction and Motivation

In this paper we study the microstructure of the MTS Global Market system, which is one of the most important European interdealer fixed income trading systems. This system is composed of a number of domestic trading platforms and a European platform (EuroMTS) on which designated bonds can be traded.[1] The trading system is fully automated and effectively works as an electronic limit order market. The structure is reminiscent of the electronic interdealer trading systems like EBS and D2002 on the FX market, but different from the quote screen-based US Treasury bond trading system. The European bond market has also a much richer menu of bonds than the US markets. Although the European capital market has integrated considerably in the last 10 years, mainly through the introduction of a single currency, European bonds can still differ in their credit rating[2].In this paper we analyze a unique new dataset at quotes and trades for the period 2001-2002.

There are a few interesting features of this trading platform. First, the MTS Global Market system is an interdealer system. In here, a market maker can pass any security to another market maker as they have the moral obligation to quote prices. This (repeated) passing of inventory is called the hot potato trading and has been analyzed by Lyons (1997). His theoretical work shows that the passing of inventory is harmful as it creates additional noise in the order flow. Hence, in order to avoid any sequence of hot potato trading, the impact of an unexpected trade in a low interdealer trading environment should have a larger impact on the price than under a high interdealer trading environment. Our dataset gives us the opportunity to test this. We find empirically that on the MTS trading platform, the impact of a trade in a low trading environment has a larger impact on price than in an environment of high trading intensity. This finding contrast the findings of Dufour and Engle (2000) and Spierdijk (2002) for stock markets. Cohen and Shin (2003) also conducted the same analysis for the US treasury market. By dividing their dataset into subsample of high and low trading intensity, they find that the effect of trades on return is higher on busy days compared to days with relative low trading intensity.

The second interesting feature of the MTS trading platform is its organizational setup. The range of securities being traded on the domestic market is by far larger than on the EuroMTS trading platform. A bond trader on the domestic MTS platform can therefore offer a much wider range of bonds to its clients. Throughout the paper, we provide a comparison of the trading costs and price dynamics on the domestic MTS markets and the EuroMTS. We show that despite the

[1] As an example, MTS France offers trading in a large range of only French debt securities including the benchmarks and highly liquid issues. On the other hand, EuroMTS only offers a smaller range of French debt issues.

[2] This varies from “AA2” for Italy to “AAA” for Austrian, Dutch, French and German bonds (Moody’s credit rating).

apparent fragmentation of trading on domestic platforms and EuroMTS, the markets are closely connected. The impact of trades is related to the issue of liquidity which is defined as the ability to trade without a significant change in the fair price of an asset. However, how to measure liquidity is somewhat harder. Fleming (2001) examines the bid-ask spread, quoted and traded size given a certain price, market volume and trading frequency for the U.S treasuries market. He finds that net order flow alone can explain a large part of the daily price movements[3]. Using this as a starting point, we provide some comparative measures of liquidity, such as quoted and effective spreads and the price impact of trades. We show that these comparative measures of liquidity are very similar for both platforms. We then turn to an analysis of the relevance of order flow for the market price dynamics. Finally, we analyze the role of trading activity, studying the effect on the order flow and return. In recent years, the empirical work on the microstructure of financial markets has received considerable attention in the academic literature. Most of the substantial empirical work in this area pertains to stock markets. Given the emphasis on stock markets in the theory and the availability of data, this is understandable. On the other hand, in terms of both capitalization and trading volume, foreign exchange and bond markets are bigger than stock markets. Research on foreign exchange and bond markets is also interesting because of their special structure. Both markets are centered around a large number of professional dealers. Outside customers trade with the dealer of their choice. Volume is high, and there is a lot of interdealer trading. The interdealer trading is even bigger than the trading with outsiders. Lyons(2002) estimates that about 2/3 of the FX trading is interdealer. Due to its obvious importance, empirical research on the microstructure of bond markets has increased in recent years. For example, Umlauf (1993), Fleming and Remolona (1997, 1999), Fleming (2001) Cohen and Shin (2003) and Goldreich, Hanke and Nath (2003) for the US Treasury market, Proudman (1995) for the UK bond markets, Albanesi and Rindi (1999) , Massa and Simonov (2001a,b) for the Italian market and Dunne et al (2002) for European Bonds.

The setup of this paper is as follows. Section 2 starts with a description of the European Bond market, the MTS trading platform and our dataset. Section 3 focuses on the study of liquidity, measured by the quoted and effective bid-ask spread. Sections 4 and 5 analyze the impact of order flows and trading intensity on the price discovery of the domestic and EuroMTS market in the 10-year benchmark bond. Section 6 concludes the paper.

[3]This has also been reported by Evans and Lyons (2001) who demonstrates that order flow is an important determinant of intra-day price movements in the foreign exchange market.

2 Description of the European Bond Market and the Dataset

This section gives a short description of the organization of the European market for sovereign bonds. The institutional environment of this market can broadly be divided into two sectors. The primary sector decides upon the finance policy based upon the funding requirement of each government. The operational activities for the implementation of these strategies is carried out by the various treasury agents like the Bundesbank for German securities, the French Tresor for French securities and the Italian Treasury for Italian debt instruments. The secondary market decides upon the trading environment. In particular, it determines the structure of payments and settlements and the trading facilities offered by brokers and market makers. Both sectors influence the price dynamics through supply and demand, where the primary sector acts as the ultimate provider of liquidity. It is therefore useful to give a description of the Eurozone government bond market based on these two sectors.

2.1 Primary Market

In a broad sense, the government bond market can be seen as the market for debt instruments with a maturity running from 2 years up to 30 years. Although we later will focus on bonds with a 10-year maturity, there is also a very active market for debt instruments with a maturity smaller than 2 years. Here, the primary sector is special as it acts as the ultimate provider of liquidity in a given government security. In the EU-money market, the European Central Bank is the ultimate supplier of monetary liquidity in the Eurozone. In contrast, every member of the Eurozone can decide its own financing operations and its supply of debt instruments. Hence, the EU-bond market is heterogeneous compared to the EU money market[4]. Table 1 shows the size of outstanding medium and long term debt which differs considerably across countries. Despite the differences in issue size, governments choose to finance their needs using debt paper with almost similar maturities.

We now describe the bond market for German and Italian debt securities in more detail. We pick these two markets as both markets are highly liquid while having different credit ratings. The German securities are rated 'AAA' while the Italian securities are rated with the 'AA2' status.

Germany The German market is the second largest bond market in the Eurozone and the fourth largest market in the world, smaller only to the United States, Japan and Italy. The government

[4]Hartmann et al. (2001) provide a detailed overview of the EU money market.

bond market has been given a strong boost since the unification of the two German states as East Germany required large financing to modernize its infrastructure.

The issues of public authorities can be categorized in a few groups from which the highly liquid Federal government bullet bonds are the most important ones[5]. In turn, the federal bonds are categorized depending on their maturity. The most popular instruments are the long-term government bonds (*Bundesanleihen or Bunds*) which have a maturity between 8 and 30 years, with the 10 year bonds being the most popular. In addition to Bunds, the federal government issues medium term notes which gained popularity since the beginning of the 1990's when foreigners were allowed to purchase these notes. These medium term notes (*Bundesobligationen or BOBL*) have a maturity of 5 years. In order to differ between the well known 5 or 10-year bonds, the German authorities introduced short term notes (*Bundesschätzanweisungen or Schätze*) in 1991 with a maturity of 2 years.

Only the Bundesbank is authorized to issue federal bonds and it publishes a calendar with the date, type and planned issue size for the next quarter. Federal bonds are issued on Wednesday using tendering where some 80% of the whole issuance is sold. The remaining 20% is set aside for market management operations and intervention. Only members of the "Bund Issuance Auction Group" are entitled to participate directly during the auction. The participants have to quote in percentages of the par value in multiples of 1 million euro with a minimum of 1 million euro. The Bundesbank expects members to submit successful bids for at least 0.05% of the total issuance in one calendar year. There are two ways in which a bond is auctioned. The first is through an American auction, a competitive bidding schedule in which the participants announce the quantity and price that they are willing to pay for the security taking a minimum price into account. The participant with the highest price will be met first followed by the second highest price, and so forth. The second method is through a Dutch auction, a non-competitive bid in which the Bundesbank determines one price through the bidding schedule of the participants.

Italy The Italian market remains one of the largest bond market in the world [6]. By now, the Italian market is by far the largest European Bond market due to its large deficit in the government budget. Since its approval of the Maastricht duty in 1991 however, the Italian government tightened its economic and monetary policy to pursue an economic environment of stable prices and solid public finances. This has its influence on the performance of Italian securities. We can see this

[5] Other bonds are for example Länder bonds and unity bonds

[6] According to the Italian treasury, the outstanding debt is around 1200 billion euro including debt issued by state authorities.

in Figure 1 where the spread between the 10 year benchmark bonds of Italy is plotted against its German equivalent[7].

The most important medium and long term bond issued by the Italian treasury are BTPs (*Buoni del Tresoro Poliennali*). These are bullet bonds with a maturity of 3, 5, 7, 10 or 30 years with coupons paid on a semi-annual basis. The vast majority of bonds in the Eurozone market are bullet bonds with fixed coupons although some bonds are successful in the floating rate market. The Italian CCT bonds (*Certificati di Credito del Tesoro*) for example are relatively successful just like the French OATi bonds. Although both bonds pay a variable coupon rate, they are calculated differently. The coupon of CCTs are based on the yield of the last issued 6 month treasury bill plus a fixed spread while the coupon rate of OATi's are based on the level of the French price index. Also, the coupon of CCTs are paid on a semi-annual basis while OATi's are paid on an annual basis.

With respect to the primary auctions, the Italian treasurer announces its auction calendar for the next year in September. The way these auctions are conducted for BTPs and CCTs is through the Dutch auction mechanism, a method already described for German securities. For the Italian markets, members can post a maximum of 5 bids where the minimum acceptable spread between the bids is at least 5 basis points.

2.2 Secondary Market: The MTS System

Let us now turn our attention to the secondary market. There are two ways in which bonds are negotiated in the secondary market of the Eurozone. The traditional way is through an organized exchange were trading has been fairly low. The second way is through the OTC market in which the main players are banks, most of them also participating in the primary auctions.

Of particular interest in the OTC market is the MTS (*Mercato dei Titoli de Stato*) system, which turned to be successful by gaining a considerable market share since its creation in 1988 by the Bank of Italy and the Italian Treasury in order to improve the liquidity of the Italian Treasury market. Nowadays MTS is managed by a private company. The MTS system is an interdealer platform and therefore not accessible for individuals. A recent quarterly bulletin by the Italian treasury[8] reports that some 6.4 billion euro of BTPs were traded on an average base in 2002 by the MTS trading platform. According to an older paper by the Italian debt office, this accounts for some 65% of all secondary market activities[9].

[7]The word 'equivalent' can be misleading as both bonds where not Euro-denominated before 1999.

[8]Quarterly bulletin-3rd quarter 2002

[9]The Italian Treasury and Securities Markets: Overview and Recent Developments. *Public Debt Management*

The original MTS market was first introduced in Italy in 1988 in order to enhance trading in the secondary market for Italian government bonds, which already existed as an over-the-counter market. In order to improve market depth and activity, MTS was reformed in 1994 which created the basis of the current MTS trading system. Privatization of the MTS system into MTS Spa took place in 1997 and later in 1999 EuroMTS was created. In 2001, both EuroMTS and MTS Spa merged into MTS Global Market, becoming the largest interdealer market for Euro-denominated government bonds. Since the end of the nineties, the MTS system expanded to other Euro-denominated markets and is now successfully operational as MTS Finland, MTS Ireland, MTS Belgium, MTS Amsterdam, MTS Germany, MTS France, MTS Portugal and MTS Spain[10]. On these platforms only Government bonds and bills are traded. In April 1999 the EuroMTS system was launched. This electronic trading platform provides trading in European government benchmark bonds as well as high quality non-government bonds covered by either mortgages or public state loans. The third stage of development of the MTS platform was the creation of MTS Credit in May 2000 where only non-government bonds are traded.

The participants in the MTS trading platform are mainly investment banks. The variety of banks is very large. Not only large investment banks like Merrill Lynch, Deutsche Bank or UBS participate but also smaller banks. Especially in Italy, the number of small regional banks is large. Although there are different requirements for participants depending on the market of operation, we can categorize all participants either as market makers or as market takers. Market makers have market making obligations as they have to quote all bonds that they are assigned to in a two-way proposal for at least five hours a day. In the early years, the system knew full transparency, but in 1997 anonymity was introduced in order to avoid "free-riding"[11]. The maximum spread of these securities are pre-specified depending on liquidity and maturity. Proposals must be formulated for a minimum quantity equal to either 10, 5 or 2.5 million Euro depending on the market and maturity of the bond. In addition, a maximum spread of these proposals exist and is pre- specified depending on the liquidity and maturity of the security[12]. Orders in round lots are executed automatically according price priority and the time that they are sent (first in first out). Odd lots are subject to

Office, March 2000.

[10]The MTS system is also operational in Japan. Because we focus on Euro-denominated markets, we leave MTS Japan out of our analysis.

[11]Massa and Simonov (2001b) showed that "free-riding" existed as the reputation of a market maker had some impact on the price process.

[12]The longer the maturity the higher the spread. The maximum spread is not binding. A marketmaker is allowed to propose a quotation larger than this maximum spread. However, activities based on these trades are not added to his performance record.

the market makers' acceptance. No obligations apply to market takers, they can only buy or sell at given prices. An interesting feature of the MTS system is the competition between market makers. Although the importance of competition between market makers has been known for a long time, some influential papers like Stoll (1978), Copeland and Galai (1983) and Kyle (1985) focus on the behavior of a single market maker. Another interesting feature of the MTS trading mechanism is the simultaneous existence of two markets where the bonds can be traded. For most securities, the market maker can post any prices on both the local MTS (like MTS Belgium, MTS Amsterdam, MTS Italy and MTS France) but also on EuroMTS.

Table 2 shows us the minimum quantity of the proposals and orders for every market in more detail. Note that the quoted proposals are firm, i.e. every trader can hit a quoted proposal and trading is guaranteed against that quote. Effectively, the MTS system therefore works as a limit order book. The live market pages offered to participants offers the following functionalities:

- *The quote page* offered to market makers enables them to insert new offers. Posted proposals can be modified, suspended or reactivated;
- *The market depth page* allows participants to see the best 5 bid and ask prices for each security chosen together with its aggregated quantity.
- *The best page* shows for all products the best bid-ask price together with its aggregated quantity;
- *The incoming order page* permits the manual acceptance within 30 seconds of odd lots.
- *The super best page* shows the best price for bonds listed on both the local MTS and the EuroMTS. This will allow market makers with access to both markets to see the best price. A market maker who has access to both markets can choose parallel quotation, i.e. simultaneous posting of proposals on the domestic and the EuroMTS platform.
- *Live market pages* shows for every bond the average weighted price and the cumulative amount being traded sofar.

Remember that all trades are anonymous and the identity of the counterparty is only revealed after a trade is executed for clearing and settlement purposes. The aggregated observed quantity is the sum of all quantities chosen to be shown by the market maker. Every market maker can post the entire quantity that he is willing to trade (block quantity) or a smaller amount (drip quantity) while taking into account the minimum quantity required. In the latter case, the remaining quantity will remain hidden to the market. For example, a market maker who has a position of EUR 50 million in a market where the minimum quantity is EUR 10 million can construct 5 drip quantities of 10 million. If we assume that he is the only market maker that time of the day, then the aggregated observed quantity as observed by the market will be 10 million. On the other hand, the market maker can post one block quantity of 50 million creating an aggregated observed quantity of 50 million euro.

We now turn to a comparison of the domestic platforms with the EuroMTS platform. The EuroMTS platform only offers trading in the running benchmark bonds while the local platforms offers trading in non-benchmark bonds as well. For example, 55 BTP bonds are traded on the Italian market while just 11 of these bonds are traded on the EuroMTS system[13]. So at first sight, the EuroMTS might seem redundant as all bonds being traded on this market are also traded on the domestic trading system. Table 3 gives us an overview of participants on the MTS trading system. As we can see in this table, the largest part of the participants are market makers creating a very competitive trading platform. The only exception can be found for the Italian market where more than 60% of all participants are market takers. Most of the market makers are also active on both platforms. With respect to the identity of the market makers, large market makers have access to both markets while smaller traders tend to participate on the local platform[14]. In addition, the large numbers of market makers active on both trading platforms suggest no competitive advantages in terms of quoting rights. However, the existence of both trading platforms suggests differences and we therefore ask ourselves the question why a market maker who has entrance to the local platforms would also operate on the EuroMTS trading platform.

In order to answer this question, a detailed study on the costs and the dynamics of price formation is needed. Before we start, however, we introduce our dataset.

2.3 Dataset

Our dataset is very detailed, as it covers every transaction of Italian, French, German and Belgian government bonds being traded on the MTS platforms from January 2001 until May 2002. The data records include the direction of the trade (buy or sell) and a very accurate time stamp. These data allow us to study a number of market microstructure issues in detail. Table 4 shows us the volume in the various markets including the number of transactions. A total of 867.901

[13] As of January 2003.

[14] Financial institutions who are designated as market makers must fulfill some financial requirements which differs among the platforms. For example, market makers for Belgian securities must have assets of at least EUR 250 mio. For the EuroMTS, market makers must have assets of minimum net worth of EUR 375 million.

trades took place reflecting more than EUR 4.9 trillion of market value. Here, the Italian bond market is by any means the largest market in our dataset. Some 83% of all transactions stems from trading activities in Italian securities. We also have trading data on the two largest AAA-rated bond markets in our dataset, France and Germany. These countries have a trading volume of some EUR 460 billion and EUR 233 billion respectively.[15] Although the German market is accepted as the benchmark for euro denominated government bonds due to the large liquidity and its triple 'A' status, the trading volume on MTS is fairly low. There are a few reasons for this. First, the Eurex Bond trading platform is comparable to MTS system and offers trading in all fixed income instruments of the federal republic of Germany and sub sovereigns fixed income bonds of Kreditanstalt für Wiederaufbau (KfW), the European Investment Bank and the States of the German Federal Government. Second, the existence of successful futures contracts on the EUREX and Liffe has provided investors a low cost margin based trading mechanism for all German bonds. For example, the Bund future is the most traded contract in Europe with an average daily trading volume of some 800.000 contracts on the Eurex reflecting an underlying value of EUR 800bn on a daily basis[16]. The last bond market we study is Belgium with a trading volume of EUR 316bn. The most important bond of the Belgian treasury are linear bonds, or OLOs as they are known after their combined acronym in French and Dutch (*Obligations Linéaire-Lineaire Obligaties*). These are straight non-callable bonds with fixed -coupon and redemption value. Table 4 shows the percentage of trading activity taken place on the local and European MTS platform. German securities are mostly traded on the European platform together with the French medium term notes. Italian and Belgian securities are rarely traded on the European platform as most transactions take place on the local platform.

There are some requirements with respect to minimum lots being traded on the different markets depending on maturity of the underlying securities. The minimum lots are at least 5 million or 10 million for benchmark securities depending on their maturity and at least 2.5 million for non-benchmark securities. It is therefore useful to analyze the trading size and volumes per type of bond rather than per market. On a country level, one finds trading size in Belgian, French and German securities being comparable with more than 7 million euro per trade. Trading in Italian securities stands at an average of 5.3 million euro. In order to get an idea of the actual trade sizes

[15]Long term French bonds are divided into OATs, fixed coupon bearing bonds with a maturity between 7 and 30 years and inflation linked bonds called OATi. Short term bonds have maturity between 2 and 5 years and are called BTANs. All these bonds are calculated on an actual/actual basis with annual coupon payments.

[16]Source Eurex website. Every bundcontract requires delivery of EUR 100.000 face value of a bond with a maturity between 8.5 and 10.5 years at the moment of delivery.

we counted the number of 2.5, 5 and 10 million trades. The results are shown in Table 5. More than 95 percent of all trades have either 2.5, 5 or 10 million of market value with the exception of the Italian securities, where there is a significant fraction of odd-lot trades. The most important reason for this difference is the relative small size of the participants on the domestic Italian platform.

3 Liquidity on the MTS Market

Our first measure of trading costs is the volume weighted quoted spread (VWQS). This is a measure of the depth of the limit order book associated to a specific transaction size, and will reflect the implicit cost for an immediate transaction of a given size. We adapted the indicator of liquidity that Benston et al. (2000) suggested for measuring the ex-ante committed liquidity of a stock market organized like a limit order book. Let B_0 denote the inside bid price and A_0 the inside ask price with $B_h > B_{h+1}$ and $A_h < A_{h+1}$ respectively. Let the euro amount of bonds offered or requested at these prices be Q_h^z with $z = ask, bid$ and let the trade size be $L = 5, 10, 25$ million euro, respectively[17]. Define the indicator I_h^z as:

$$I_h^z = \begin{cases} 1 & \text{if} & L > \sum_{i=1}^{h} Q_i^z \\ Q_h^{-z}\left[L - \sum_{i=1}^{h} Q_i^z\right] & \text{if} & \sum_{i=1}^{h-1} Q_i^z < L < \sum_{i=1}^{h} Q_i^z \\ 0 & \text{if} & \text{otherwise} \end{cases} \tag{1}$$

The volume weighted quoted spread associated to a trade size equal to L is

$$WQBAS(L) = \frac{2\left[\sum_{i=0}^{\infty} I_h^{ask} A_h Q_h^{ask} - \sum_{i=0}^{\infty} I_h^{bid} B_h Q_h^{bid}\right]}{L\left(A_0 + B_0\right)} \tag{2}$$

Table 6 reports the Volume Weighted Quoted Spread measure for class A, B, C and D benchmark bonds for Belgium, France, Germany and Italy, on the domestic and EuroMTS platforms[18]. Our findings are that the quoted spread is similar across countries and for class A and B bonds, around 2 or 3 basis points from the best prevailing midquote. For class C bonds, the quoted spread is slightly higher than for the A and B class. The Italian market is more liquid than the others for class C bonds, probably because it includes the heavily traded 10-year BTP bond. The quoted spread is substantially higher for the longest maturity bucket D (13.5 to 30 years), ranging from 11 to 18 basis points, depending on maturity and country. This pattern is consistent with the findings in Amihud and Mendelsohn (1991), who show that the bid-ask spread is higher in US treasury notes compared to more liquid US T-bills.

[17] These transaction sizes are the most frequently traded in MTS Global Market.

[18] Since we don't have the order book data for 2001, the estimates are based on data from 4-8 and 11-15 February 2002.

An interesting finding is that the market is very deep, i.e. the quoted spread for large orders is only marginally bigger than the quoted spread for standard size orders. For example, for the Italian 10 year benchmark bond the quoted spread for a standard 5 million trade is 3 basis points, for a large trade of 25 million the quoted spread is still below 4 basis points. This pattern is similar for the other bond classes and countries. In practice, trades larger than 10 million Euro are rare. Observe that the quoted spreads on the EuroMTS platform are always slightly bigger than on the domestic MTS platforms, but the pattern across bond classes and countries is exactly the same as on the domestic MTS systems.

Of course, the quoted spread may include periods where there is little trading and may give a inaccurate indication of actually incurred trading costs. Therefore, we also calculate measures of the effective spread. The effective spread is defined as twice the difference between the transaction price and the midpoint of bid and ask quotes

$$\hat{S}_{eff} = \frac{1}{T}\sum_{t=1}^{T} 2I_t(p_t - m_t) \tag{3}$$

where p_t is the transaction price, m_t the prevailing midquote at the time of the trade, and I_t the buy/sell indicator ($I_t = +1$ if the trade is initiated by the buyer, $I_t = -1$ if it is initiated by the seller). In our dataset we do not always observe p_t and m_t exactly at the same time, but we select the midquote that in time is closest to the time of the transaction. The realized spread compares the transaction price p_t and the subsequent midquote, m_{t+1}. Here we use a similar definition,

$$\hat{S}_{realized} = \frac{1}{T}\sum_{t=1}^{T} 2I_t(p_t - m_{t+1}) \tag{4}$$

It is obviously not always the case that the trade price is above/below the subsequent midprice for buyer/seller initiated trades, as the market may have moved. Therefore, the realized spread measure may be negative.

Table 7 shows the estimates of effective and realized spread. The table shows that the realized spread is always smaller than the effective spread. The numbers, however, are sometimes quite large and the estimates of the effective spread are probably not very accurate due to the mismatch in time between trade and midquote. Table 7 also provides the outcome of testing whether the effective (realized) spread on the EuroMTS is significant different from the effective (realized) spread on the domestic platforms. As we can see, there can be a difference in realized spreads but this only occurs for a small number of bonds. We now turn to a final measure of the spread. We use a measure that is based on transaction prices only: the spread based on absolute price changes between two transactions

$$S_{APC} = \frac{1}{n} \sum_{t=1, j \neq z}^{n} \left| p_{t+1}^{j} - p_{t}^{z} \right| \tag{5}$$

where $j = ask, bid$ and $z = bid, ask$. Table 8 reports estimates of the spread based on absolute price changes for the same menu of bonds as before. The results confirm the pattern that we found for the quoted spreads. Estimated spreads are increasing with maturity, and on average are slightly higher on EuroMTS. Moreover, the estimated spread of the long bonds is somewhat smaller in the Italian securities compared to the estimated spread in Germany and France. Figure 2 shows the same information graphically. Table 8 also included a test to see whether there exist a significant differences between EuroMTS and the local trading platform. Some differences exist but the overall conclusion is that spreads among the platforms are the same.

Finally, we take a quick look at intraday spread patterns. Figure 3 shows the intraday pattern of quoted spreads for the most actively traded issue, the Italian 10-year bond. The quoted spreads shows a typical U-shaped pattern, the trading day kicks off with a relative large spread around 3 basis point in the early morning, falling to 2 basis points in the late morning and gradually increasing to 4 basis points in the late afternoon. Figure 4 shows the intraday pattern of effective and realized spread for the 10 year Italian bond. Again, a U-shaped pattern is being observed in here as well. Summarizing these results, we conclude that the quoted spread across countries is similar for bonds with a short maturity. For long term bonds differences exist. At first sight, the data suggest that the quoted spread varies over time while being lower on the domestic platforms. Effective spread estimates based on transaction prices show a very similar patter across maturities. However, when testing differences in spreads between the domestic and EuroMTS platforms, we find that differences exist for a just few bonds and in general, both markets are very integrated. The MTS order book for these benchmark bonds is also very deep as the quoted spreads are only marginally different for larger trade sizes. By analyzing intraday patterns of the spread, we find that the quoted spread show a U-shaped pattern.

4 The Price Impact of Trading

The previous section provided us some insights in the pricing behavior of market makers on the MTS trading platforms. However, some of the analysis is based on just one month of (quote) data and perhaps not representative for the whole dataset. From an economic point of view, we would like to have an idea of the causes of the bid-ask spread and the price impact of orders. It is therefore useful to analyze the impact of trades on the price process while at the same time taking into account the different aspects of trading costs. In order to do so, we apply the model proposed by Glosten and Harris (1988) which explicitly takes the role of adverse selection and transaction costs into account. Later we add the impact of trading intensity and analyze how this influences the price discovery on the MTS trading platforms.

From the perspective of the MTS structure, prices proceed orders. Therefore, we can expect *a priori* an impact of price on the orders posted by market makers. Order flow is important for several reasons. Stoll (1978) and O'Hara and Oldfield (1986) show that an incoming order will always cause a change in the position of the market makers inventory as they are obligated to offer liquidity [19]. For this, they want to be compensated by a bid-ask spread. The larger the transaction size, the larger the shift will be towards a possible unfavorable position, requiring an even larger compensation as shown by Easley and O'Hara (1987). Second, order flows affects prices as the aggregated order flow reflects market sentiment. For example, a positive accumulation of order flows means that there were more "buy" orders than "sell" orders, reflecting a "bullish" sentiment on the market. Third, from an information point of view, one can argue that asymmetric information induces larger "buy" or "sell" orders because informed market participants will trade as much and as fast as possible before the information is made public. Even if the market is driven by publicly known fundamentals, order flow contains private information as it depends on the beliefs formed by market participants while being known only by their market maker. This has been shown by Evans and Lyons (2001, 2002), who analyze the impact of order flows on prices in the FOREX market. Traditionally, this market is analyzed using publicly known macro-economic factors. By using order flows as a proxy for private information, they show that order flows are positive correlated with macro economic announcements and hence an aggregation of information in these markets.

In order to measure the effect of trading costs in the price process, we use a model as suggested by Glosten and Harris (GH, 1988). Although the models original setup is based on a single market maker framework, it is useful as a first step to measure the effects of costs and order flows on the price dynamics. GH assume that the spread can be decomposed into two components: a transitory component, which is unrelated to the true value of the security; and an adverse selection component which is correlated with the true value of the security. In here, we assume that transaction cost are independent of the quantity being traded while the adverse selection component is correlated with the order flow. In addition, we assume that the underlying price process is the same for the domestic and EuroMTS platform. However, temporary differences in price and price impact is

[19] Although market makers can refuse to quote, this happens rarely. Not quoting in this market is often seen as a serious offend, harming the reputation of the market maker.

allowed for which we introduce a dummy variable D_t which indicates 1 when a trade occurred on the EuroMTS and 0 otherwise. Specifically, the dynamics of the is given by:

$$\begin{aligned} P_t &= \xi_t + I_t C_t \\ \xi_t &= \xi_{t-1} + e_t + I_t Q_t \\ A_t &= (a_1 + \delta^{\alpha} D_t)\, Q_t \\ C_t &= c_0 + \delta^{c} D_t \end{aligned} \tag{6}$$

The system of equations as given by (6) assumes that the price dynamic P_t is determined by an efficient price component ξ_t and a transitory cost component C_t. The efficient price component ξ_t is determined by its one period lag and a variable e_t, which reflects the arrival of public information. Here I_t indicates 1 if the trade is a "buy" and -1 if the trade is a "sell" and $I_t Q_t$ denotes the signed quantity being traded at time t. We assume that e_t has a distribution with zero mean and variance σ^2. We also use an adverse selection component A_t which is a function of the traded quantity. The model as given by (6) cannot be estimated as the efficient price is not observed. However, one can express the reduced form of system (6) in terms of quote revisions:

$$\triangle P_t = \alpha + c_0 (I_t - I_{t-1}) + \delta^{c} (D_t I_t - D_{t-1} I_{t-1}) + a_1 I_t Q_t + \delta^{\alpha} D_t Q_t I_t + e_t \tag{7}$$

We estimate equation (7) using OLS with heteroskedastic consistent White standard errors. The bonds that we consider for our estimation purposes are the 10-year benchmark bonds of Belgium, France, Germany and Italy. We consider these bonds in more detail in Table 9. The reasons to consider these bonds is threefold. First, these running benchmark bonds are being traded on both trading platform. Second, the number of observations for these countries and bond series is the largest and therefore more suitable for statistical inference. Third, the 10-year area of the European yield-curve is very active in terms of trading activity and issuance by government agents. It is also considered to be the most important long bond on the yield curve. The estimation results are reported in Table 10. We discuss these results per country.

The Italian market show a positive and significant c_0 and a_1. A positive c_0 parameter indicates that that market makers require a compensation for their market making services as they face trading cost. Also, the positiveness of a_1 indicates that the larger the quantity involved in the transaction, the larger the price will change. In addition, the a_1 parameter also reflects the information component. The higher the informational content of a trade, the more aggressive pricing will occur in order to avoid disadvantages due to information asymmetry. Using the estimated values we find that the total cost for a EUR 5 million trade of the BTP 2011 bond equals $2\,(c_0 + a_1 Q_t) \approx 2\,(0.29 + 5 \times 0.06) = 1.2$ basis points.

The Belgian market shows also a positive and significant fixed costs coefficient c_0 but is somewhat larger ($\approx$ 0.5 basis points) than the estimated value in Italian securities($\approx$ 0.3 basis points). It is important to understand this difference as it reflects the fees paid for trading on the different domestic MTS platforms. The cost structure for MTS participants is a decreasing function of annual turnover and the large trading activity in Italian securities may contribute easier to these lower fixed cost[20]. Because we cannot find any evidence of a positive a_1 coefficient here, we conclude that the cost for trading 5 million or 10 million in the OLO 2011 bond is the same, equaling $2c_0 \approx 1.0$ basis points.

The German market shows only a positive and significant a_1 parameter for the 2011 bond while no statistical evidence exist for the 2012 bond. The cost associated with trading 5 million is therefore $2a_1Q_t \approx 2\,(0.3 \times 5) = 3.0$ basis points. This is significantly higher compared to e.g. the Italian securities.

The French market does not show any evidence of significant trading costs.

The estimation results in Table 10 show no proof of significant difference in trading between the EuroMTS and the domestic French and Belgian trading platform. But for the German and Italian market the fixed cost component in higher on EuroMTS ($\delta^c > 0$). On the other hand, the adverse selection cost is lower on EuroMTS for the Italian bonds ($\delta^a < 0$).

An important question in our analysis is the difference between the EuroMTS and the domestic markets. Notice that a trader will prefer to trade on the local market if the cost of trading in the local platform is smaller than on the EuroMTS.

$$E(\Delta P_t^{local}) < E(\Delta P_t^{EuroMTS}) \Rightarrow A_t^{local} + C_t^{local} < A_t^{EuroMTS} + C_t^{EuroMTS} \tag{8}$$

Let $Q_t^* = -\delta^c/\delta^\alpha$ denote the quantity for which the trader is indifferent between trading on the local or EuroMTS platform. Clearly, a trader will prefer to trade a quantity Q_t on the local market if $Q_t^* < Q_t$ for $\delta^\alpha > 0$ and $Q_t^* > Q_t$ for $\delta^\alpha < 0$. Using the estimates of the BTP 2011 bond, we find that $Q_t^* = 2.83$. From the previous section we know that more than 96 percent of all trades is at least 2.5 million euro and it looks like the trading costs on the Italian platform is smaller as long as the quantity being traded is below 2.84 million. This difference however is small but significant for quantities larger than 3.5 million[21]. As an illustration, consider a 5 million trade in this bond. If this trade takes place on the EuroMTS the trading costs is approximately is $2\,(\delta^\alpha Q_t + \delta^c) \approx 2\,(-0.03 \times 5 + 0.09) = -0.12$ basis points, i.e. 0.12bp smaller compared to the

[20] We do not know exactly the amount which a market maker needs to trade in order to face a substantial decline in trading fees but it should be different across markets.

[21] A Wald test is used to test the null-hypothesis $Q\delta^\alpha + \delta^c = 0$. At 5% significance, 3.5 million is still accepted.

same trade on the local platform. Note however, that the differences are very small. For the other bond series, we do not document any significant differences between trading cost at the domestic platform and EuroMTS.

To see why differences in trading cost may occur, we have to look at the organizational structure of the MTS platform. Market makers are shareholders of the local MTS market (e.g. some market makers are shareholders of MTS Amsterdam, MTS Germany etc.) and are therefore entitled to receive a part of the profit. Another explanation may be that some large, international dealers are only present on EuroMTS and not in the local markets, and smaller local dealers often only trade in the domestic markets. These trading patterns may induce small differences in effective spreads and trading costs. A detailed study where we take into account the identity of local versus EuroMTS players would be interesting and is work for the future.

5 Price and Order Flow Dynamics on the MTS Platform

Although the Glosten-Harris model provides useful insights into the role of costs and adverse selection in the price process, it lacks a full dynamic framework. This is important as market makers on the MTS trading platforms are able to extract information from the live market pages of the system[22]. Therefore, the process of market making not only depends on the concurrent price and trade but also on the previous change in prices and lagged order flows. Hence, time varying price discovery exist depending on the past history up to a trade. Also, lagged traded quantity is also important as the MTS trading system allows the splitting of orders and it is likely that the observed order book is the drip quantity instead of the total (block) quantity. Therefore, the interaction between order flow and price requires a more dynamic setup of the Glosten-Harris model in order to capture the endogenous relation between (passed) order flows and prices. For this, the level of activity on the MTS platform is important to take into account as well. The larger the trading intensity (i.e. the number of trades in a certain time interval) the more information the market maker receives from its market pages.

The theoretical literature is not unanimous about the effect of trading intensity on price discovery. From the information based approach, one can argue that informed market participants want to trade as much and as fast as possible without being detected. Hence, informed traders will trade as much as possible when the number of noise traders is large (Kyle, 1985) or trading intensity is high (Easley and O'Hara, 1992). They argue that there exist a positive relationship between

[22]In the MTS platform, a market maker receive market updates with respect to cumulatives quantity (not signed) and the weighted average price from the past 5 minutes in the running hour.

information and trading intensity as more informed traders are active during high market activity. Therefore, larger price impacts will occur during periods of high trading intensity or a lower impact on price when trades arrive after a longer period of inactivity. On the other side, Diamond and Verrechia (1987) argue that informed traders always trade, no matter what the nature of the information is as they can take long or short positions. However, if short sale constraints exist, bad news takes more time to reveal resulting in lower market activity or trading intensity. Hence, a longer period of trade absence increase the probability of facing an informed trader with bad news who is constrained from selling short. Therefore, they expect a negative relationship between information and trading intensity (more informed traders will trade during low trading intensity) and hence a negative correlation between price discovery and trading intensity (higher impact of trades arriving after a longer period of inactivity). In addition, the interdealer setup of the MTS market gives us the opportunity to analyse the impact of repeated inventory passing or hot potato trading. Lyons (1997) presented a theoretical model and shows that the repeated passing of inventory is harmfull as it creates additional noise in the order flow. We therefore expect the impact of an unexpected trade in a quiet trading environment having a larger impact on the price than under a busy trading environment. From the perspective of inventory control, price discovery is negative correlated with trading intensity as the ability to control inventory is easier during high market activity. A classic article by Garman (1976) expects market makers to control the entering of traders by adjusting their bid and ask price. There is less need to adjust the spread as traders enter the market on a frequent basis during high market activity.

Based on equity data, Dufour and Engle (2000) showed that a higher trading intensity is related to stronger price impacts. They suggest that a larger trading size or trading intensity is likely to be an informational event as the market maker increase its bid ask spread in response to trades. The same results are reported by Spierdijk (2002). She shows using NYSE stock trading data that with a high trading intensity, a new trade has indeed a larger impact on prices. In order to analyze price changes and order flow in a more dynamic setup, we use the VAR model as introduced by Hasbrouck (1991a). This model is a system of two dynamic equations, one for price changes (returns) and one for signed quantities, with lagged values of both variables as explanatory variables. This model allows us to analyze the interaction between order flow and returns in the form of impulse responses of a shock (an unexpected trade) to the trading process. Dufour and Engle (2000) extended the Hasbrouck model by making the coefficients of the VAR model time-varying. Following Dufour-Engle, we make the coefficients a function of trading intensity, defined as the reciprocal of the number of minutes between two trades. We also make the coefficients depend on the location of the trade, i.e. whether the trade was done on a domestic platform or on

EuroMTS.

Intraday data typically contain very strong diurnal patterns. Engle and Russel (1995) documented higher volatility at he beginning and end of the day with similar patterns for volume and spreads. In order to capture some of these patterns, we correct duration for intraday seasonality. The exact procedure is as follows: we divide our dataset in 17 intervals running from [8.30-9.00) to [17.00-17.30). Prior to estimation, we skip the durations between market close and the next day's opening. Our indicator for trading duration in interval τ is given by $T_{t,\tau}$ which is the time in minutes between trade t and trade $t-1$[23], $t \in \tau$. The trading duration is now corrected for diurnal patterns by dividing by the average trading duration in interval τ as given by $\bar{T}_\tau$.Although we use the term trading intensity throughout the paper, we must keep in mind that this is inversely related to $\ln T_{t-i}$. In other words, the higher $\ln T_{t-i}$, the longer the duration was between trade t and $t-1$ and hence the lower the trading intensity. With these ingredients, the full model is

$$\begin{aligned} r_t &= \bar{\alpha}^r + \sum_{i=1}^{P}\left(\bar{\beta}_i^r + \bar{z}_i^r \ln \frac{T_{t-i,\tau}}{\bar{T}_\tau}\right) r_{t-i} + \sum_{i=0}^{P}\left(\bar{\gamma}_i^r + \bar{\delta}_i^r D_{t-i} + \bar{\tau}_i^r \ln \frac{T_{t-i,\tau}}{\bar{T}_\tau}\right) Q_{t-i} + \varepsilon_{1,t} \qquad (9) \\ Q_t &= \bar{\alpha}^Q + \sum_{i=1}^{P}\left(\bar{\beta}_i^Q + \bar{z}_i^Q \ln \frac{T_{t-i,\tau}}{\bar{T}_\tau}\right) r_{t-i} + \sum_{i=1}^{P}\left(\bar{\gamma}_i^Q + \bar{\delta}_i^Q D_{t-i} + \bar{\tau}_i^Q \ln \frac{T_{t-i,\tau}}{\bar{T}_\tau}\right) Q_{t-i} + \varepsilon_{2,t} \end{aligned}$$

where $r_t = 10000 \ln(P_t/P_{t-1})$ and Q_t is the signed quantity in millions of Euro's of the notional amount. Hence, Q_t is negative when a 'sell' occurred while being positive in case of a 'buy'. The coefficients are a function of the duration since the previous trade, T_t, and a market dummy D_t which takes the value 1 if the trade at t occurred on the European MTS and zero otherwise. Notice that the equation for the returns contains a contemporaneous effect of the signed trade quantity. For the identification of the model we therefore assume that the error terms are mutually and serially uncorrelated.

5.1 Empirical Results

In the estimation, we truncated the lagged variable at $p = 3$. Because of the likely presence of heteroskedasticity we report White heteroskedastic consistent standard errors for statistical inference. Further details of the estimation are given in the appendix. In order to preserve space, we focus our discussion on the BTP 2011 bond which is the most actively traded bond in our dataset. The estimation results can be found in Table 11.

[23]We add one second to the observed duration, because some trades have exactly the same time stamp but a different transaction price.

5.1.1 Return Equation

The effects of trades on the quote revision r_t are considered here. The most important set of parameters for our investigation are γ_i^r, δ_i^r and τ_i^r, which are the signed quantity indicator, market indicator and the interaction between signed quantity and duration. The interaction between signed quantity and return is reflected in the γ_i^r parameter. First, note that $\gamma_0^r = 0.113$. This indicates an instantaneous upward (downward) price movement when a buy (sell) order occurs. The magnitude depends on the quantity being traded. Interesting are the results for the lagged variables $\gamma_2 = 0.004$ and $\gamma_3 = 0.003$ which are both positive and significant at a 10% confidence interval. Significant lagged effects of trading volume of price returns were also found by Manaster and Mann (1996) for futures on the CME and they argue that this is consistent with active position building. Recall however that there is not much variability in the quantities being traded as most trades are executed in units of 5 or 10 million euro.

With respect to the market indicator, we find that $\delta_0 = -0.025$ is significant and negative while all other lagged market indicators are not significant. This means that (ceteris paribus) a buy trade at time $t = 0$, i.e. $Q_0 > 0$, has a lower instantaneous impact on price relative to the same trade on the local MTS market. Recall that the dependent variable is $10000 \ln(P_t/P_{t-1})$ and the total impact of a one million 'buy' trade on the EuroMTS platform is therefore $\gamma_0 + \delta_0 = 0.113 - 0.025 = 0.088$ or 0.44 basis points for a 5 million euro trade. On the other hand, the same trade has an impact of 0.565 basis points on the local platform resulting in a difference of approximately 0.12 basis points, which is the same as the value found in the Glosten-Harris model. The z_i^r parameter relates the change in r_t and its own lagged values. Table 11 shows us that its lagged variable is important and significant at a 10% confidence interval.

The most important parameter for our analysis would be τ_i^r as it indicates the interaction of duration and signed quantity on return. Our estimates shows that the $\tau_0^r = 0.046$ and $\tau_1^r = -0.006$ are significant. In other words, the larger the quantity being traded, the stronger the instantaneous price reaction. This reaction will be even stronger when trading intensity is low. To see the instanteneous price reaction on the *local* platform, consider a duration ς^*. Our estimated findings suggest that the expected instantaneous price reaction on a local market is given by $(\gamma_0 + \tau_0^r \ln(\varsigma^*)) = 0.113 + 0.046 \ln(\varsigma^*)$. On the other hand, $\tau_1^r < 0$ indicates an increase in price when the previous quantity was a "sell" and a decrease in price when the previous order was a "buy". Because we find a positive τ_0^r we argue that a transaction arriving after a long interval has a stronger impact on trades than a transaction after a short interval. This is in contrast to the findings of Dufour and Engle (2000) or Spierdijk (2002) who both find a stronger impact after a short time interval.

There can be a few reasons for the differences in the effect of duration between stock and bond markets, which we can relate to the interdealer literature. First, bond markets reacts largely on the arrival of public information, as shown by Fleming and Remolona (1997). However, Lyons (1997) and Evans and Lyons (2002) show that client based order flows are a source of private information. Periods of high market activity on the (interdealer) MTS platform goes together with (non-interdealer) trading outside the MTS platform. Hence, during these periods, market makers are accumulating their order flows and construct beliefs based on these flows. In order to attract order flow from outside the MTS system during busy periods, the market maker will narrow his spreads[24]. The efficiency of the Bond market however, will result in almost the same or even lower spread level on the MTS platforms. Second, the passing of any inventory imbalances between market makers is the "hot-potato" game and analyzed by Lyons (1997). A period of high trading intensity on the MTS market is a sign of strong "hot-potato" trading. Lyons shows that this repeated passing of imbalances creates additional noise in the order flow. The fact that trading intensity is low simply means that market makers have no need to trade with each other and any incoming trade will be done at a large spread to avoid a sequence of 'hot potato' trading. Third, a low trading environment will increase the cost of searching for a counterparty[25]. These costs are already known from the limit book literature (e.g. Foucault et al. (2001) and Parlour (1998) and the references therein). A market maker can wait until a trader comes in with probability smaller than one or trade with another market maker on the MTS system with probability one. The cost of this sure execution is the fact that you cannot sell (buy) at your own bid (ask) price. Instead, the transaction occurs at the other market makers ask (bid) price. This is also reflected by a negative τ_1^r component where prices go up in order to decrease the probability that the upcoming trade is also a 'sell' given the previous trade was a sell.

Another possible explanation for the duration effect is the lumpy nature of the information flow in bond markets. Fleming and Remolona (1997) and Fleming (2001) show that large bond markets moves are typically caused by macro-economic news announcements. These news event happen only infrequently. Moreover, before a scheduled news announcement there is almost no trading. When the news arrives, the market responds strongly and prices jump to the new equilibrium quickly, under heavy trading. This pattern of lumpy information flow and the associated price and volume movements is consistent with the duration effects that we document: after long durations, we find

[24]This strategy has also been addressed by Madhavan (1995) who argues that traders can narrow spreads in order to attract informed order flows. Afterwards, spreads are widened again.

[25]This point was also pointed out by Flood et al. (1999) in an experimental setting.

a larger price impact of trades and less correlation in the direction of the order flow.

With respect to the results of the return equation for the other 2011 bond series[26], we do find differences between the domestic platform and EuroMTS in these markets; the δ_0 parameter is significant for Belgium ($\delta_0 = 0.067$) and Germany ($\delta_0 = -0.226$). This explains the fact that Belgium bonds mostly being traded on the local market while the German bonds are traded on the European platform. We do find a positive γ_0^r for the other bond series, which runs from 0.007 for Belgium to 0.39 for Germany. The lagged variables γ_i^r are all not significant. We find a significant τ_0 parameter for Belgium ($\tau_0 = -0.047$) and France ($\tau_0 = 0.035$). Note that the Belgian parameter is positive which means that the impact of a trade during a period of high trading intensity is larger.

Turning our attention to the 2012 bond series, we see that the reported results hold as well for the BTP 2012 bond. Here $\tau_0 = 0.054$ and again, a trade after a quiet period has a larger impact on price compared to the same trade in a busy period. Again, δ_0 is negative and equals 0.057 and the total impact of a one million 'buy' trade on the EuroMTS platform is therefore $\gamma_0 + \delta_0 = 0.144 - 0.057 = 0.087$ or 0.44 basis points for a 5 million euro trade. The same trade has an impact of 0.72 basis points on the local platform resulting in a difference of approximately $0.15bp$. For the other 2012 bond series, we cannot find any significant τ_0 and δ_0.

Our overall conclusion is that there is no clear evidence that both trading platforms are segmented. It looks like both markets are rather integrated for benchmark bonds. The only exception in this case is the MTS platform for Italian fixed income securities. The estimation results there suggest that the EuroMTS platform should offer better price discovery for large trades.

5.1.2 Quantity Equation

Let us now focus on the effect of trades on the quantity equation. As in the return equation, we estimate the model using heteroskedastic consistent standard errors. Again, we base our discussion on the estimation results for the Italian 2011 bond. First, signed trade volume exhibits strong autocorrelation. The constant in our regression model is positive and significant differently from zero. The γ_i^Q parameters are all positive and significant. A buy (sell) order is likely to be followed by some additional buy (sell) orders. This is also confirmed by the results of Hasbrouck (1991a) and Dufour and Engle (2000). This effect is even stronger on the EuroMTS platform for the BTP 2011 bond as $\delta_i > 0$ and significant for all lagged flows. Interesting are the estimates of the duration coefficients τ_i^Q which are negative and significant. The conclusion that $\gamma_i^Q > 0$ is that "buy" is likely accompanied by a another "buy" but the fact that $\tau_i^Q < 0$ reflects the fact that this likelihood

[26]To preserve space, we do not present their estimation results. They are available upon request

will decrease when the time between the trades increases. In other words, buy orders are likely to be accompanied with further buy orders but this pattern decreases when duration is longer and activity is lower. This implies a weaker positive autocorrelation of signed trades when trading activity is low[27].

Because the estimation results for both 2011 and 2012 bonds suggest some interaction between duration, signed quantity and price impact we test whether these coefficient are jointly zero in the return equation using a Wald test based on the White estimator. The results of this test is shown in Table 12. Specifically, we test whether $\tau_0^r = \tau_1^r = \tau_2^r = \tau_3^r = 0$, which is $\chi_{(4)}$ distributed under the null hypothesis. The null hypothesis is rejected for the Belgian 2011 and French 2011 bonds and the only time series being consistent are the Italian bonds.

5.2 Impulse Response Functions

In order to analyze the price and trade volume dynamics we calculate the impulse response function using the estimated coefficients for the local trading platform[28]. Specifically, we are interested in an unexpected shock in the signed quantities innovation and its impact on return and signed quantity when an unexpected buy trade of EUR 5mio occurs in the market. Here, we use the average trading intensity for analyzing the systems dynamics and the model changes into

$$\begin{aligned} r_t &= \bar{\alpha}^r + \sum_{i=1}^{P} \bar{\beta}_i^r r_{t-i} + \sum_{i=0}^{P} \bar{\gamma}_i^r Q_{t-i} + \varepsilon_{1,t} \\ Q_t &= \bar{\alpha}^Q + \sum_{i=1}^{P} \bar{\beta}_i^Q r_{t-i} + \sum_{i=1}^{P} \bar{\gamma}_i^Q Q_{t-i} + \varepsilon_{2,t} \end{aligned} \tag{10}$$

which is the VAR model that Hasbrouck (1991a) used. Again, we focus our discussion on the impulse response functions of the Italian securities which are given in figure 5 and 6. The figures also shows the impulse response function when a trade occur in a period with high trading intensity (straight line) and in a period with low trading intensity (dotted line). In the high trading intensity case, we pick a trade with $T_{t-i,\tau}$ on the 10^{th} quantile and, in case of low trading intensity, we pick a trade with $T_{t-i,\tau}$ on the 90^{th} quantile. As we can see, the initial response at time $t = 1$ is much larger during a period of low trading activity. The appendix gives us some details of impulse response functions in these cases.

An unexpected buy trade results in a positive response as a buy will always be traded on the ask side. Note that the initial impact of a buy trade is much larger when the market is quiet, i.e. the time between trades is large and the lowest impact on the price process occurs when trading

[27] These effects are also found for the BTP 2012 bond.

[28] The appendix provides details on the calculation of the impulse responses.

intensity is high. As we can see in the figures,an unexpected positive shock results in a instantaneous upward price movement between 0.4bp to 0.6bp for the BTP 2011 and 0.4bp to 0.9bp for the BTP 2012. The bid-ask bounds arises in the 2nd trade which will cause the impulse response function to move downwards. However, the estimations suggested a positive correlation between order flows and a buy order is likely to be followed up by additional buy orders and the system therefore does not instantaneous move back to its equilibrium, instead it takes approximately 9 trades before the system is back to its equilibrium. The permanent effect of a initial buy on the price process is positive as shown by the accumulated response function. As we can see, the permanent impact runs from 0.45bp to 0.9bp with a highest impact for periods in which trading intensity is low followed by average and high trading intensive periods.

Cohen and Shin (2003) also analyses the impact of trades on return using impulse response functions for the US treasury market. Their VAR estimations are based on different subsamples of high and low trading intensity. They find that the impact on return on high trading intensive days is larger compared to days of low trading intensity. However, their approach is somewhat different as they do not take into account the irregular time interval between observations and the diurnal patterns observed. Interesting is their analysis of impulse response function for February 3, 2000 which was a very volatile day with a lot of uncertainty in the market. The nature of this shock, which occurred the day before[29], was so unique that uncertainty still existed several days after. Our approach however does not isolate volatile days, instead it averages the trading intensity throughout the dataset.

6 Conclusions

This paper offers some insights in the microstructure of the European government bond market. We have studied the mechanics of price formation on the MTS trading platform. This platform is the largest pan European interdealer bond trading system in which market makers are obligated to quote two sides. Our analysis focuses on the benchmark bonds of Belgium, France, Germany and Italy.

Our discussion has been divided into two parts. First, we measure trading costs using static measures such as the quoted spread, the effective spread and the realized spread. The results show that the spreads in the bond market are very small, between 1 and 3 basis points for the issues with maturities up to 10 years. The 30 year issues have somewhat higher spreads. The

[29]On February 2, the Treasury announced the reduction of future supply in especcially the long end of the curve. This resulted in a significant flattening of the curve in the 10-30yr area.

spreads are smallest for the most actively traded issues such as the Italian 10 year bonds. There are small differences between the spreads on the MTS domestic trading platforms and EuroMTS. The domestic markets typically offers slightly better spreads, both quoted and effective although differences are small.

We then turn our attention to the price impact of trades and trading duration. We use the Glosten-Harris model to analyze the role of trading costs and adverse selection on price changes. The estimation results suggest that transitory trading costs are important for Belgian and Italian securities, and adverse selection cost are important for all markets. Based on the estimates we cannot find any differences between both trading platforms. Only the Italian 2011 bond shows some differences in favor to EuroMTS when larger amounts are traded. However, this difference is rather marginal.

We also analyze price discovery by adding parameters of trading intensity and lagged order flows, utilizing the Dufour-Engle model. The results show that order flow is an important determinant of price fluctuations on the bond market. Also, trading intensity plays a key role. In contrast to findings for stock markets, we find a higher price impact of trades after long durations, and lower price impacts when trading activity is high. We also find that the order flow becomes less correlated after long durations.

A Econometric details

This appendix gives details on the econometric methods used in the Dufour-Engle model. Instead of estimating model (9) per equation, we estimate the model as a dynamic simultaneous equation model. Following Hasbrouck (1991a), we first rewrite the model into vector notation

$$\mathbf{Y}_t = \sum_{i=1}^{P} \bar{\mathbf{A}}_i \mathbf{Y}_{t-i} + \bar{\mathbf{a}} + \sum_{i=1}^{P} \bar{\mathbf{B}}_i \mathbf{X}_{t-i} + \sum_{i=0}^{P} \bar{\mathbf{C}}_i D_{t-i} Q_{t-i} + \bar{\mathbf{G}} \mathbf{Y}_t + \bar{\mathbf{F}}_0 \ln T_t Q_t + \boldsymbol{\varepsilon}_t \tag{11}$$

where

$$\mathbf{Y}_{t-i} = \begin{bmatrix} r_{t-i} \\ Q_{t-i} \end{bmatrix}, \mathbf{X}_{t-i} = \begin{bmatrix} \ln(T_{t-i,\tau} \bar{T}_\tau^{-1}) r_{t-i} \\ \ln(T_{t-i,\tau} \bar{T}_\tau^{-1}) Q_{t-i} \end{bmatrix}, \tag{12}$$

and

$$\bar{\mathbf{a}} = \begin{bmatrix} \bar{\alpha}^r \\ \bar{\alpha}^Q \end{bmatrix}, \bar{\mathbf{A}}_i = \begin{bmatrix} \bar{\beta}_i^r & \bar{\gamma}_i^r \\ \bar{\beta}_i^Q & \bar{\gamma}_i^Q \end{bmatrix}, \bar{\mathbf{B}}_i = \begin{bmatrix} \bar{z}_i^r & \bar{\tau}_i^r \\ \bar{z}_i^Q & \bar{\tau}_i^Q \end{bmatrix}, \tag{13}$$

$$\bar{\mathbf{C}}_i = \begin{bmatrix} \bar{\delta}_i^r \\ \bar{\delta}_i^Q \end{bmatrix}, \bar{\mathbf{C}}_0 = \begin{bmatrix} \bar{\delta}_0^r \\ 0 \end{bmatrix}, \bar{\mathbf{F}}_0 = \begin{bmatrix} \bar{\tau}_0^r \\ 0 \end{bmatrix}, \bar{\mathbf{G}} = \begin{bmatrix} 0 & \bar{\gamma}_0^r \\ 0 & 0 \end{bmatrix} \tag{14}$$

Here the $\mathbf{Y}_t$ variables are endogenous as it contains the output of the system while $\mathbf{X}_t$ contains the observable input variables and therefore being exogenous. The reduced form of the t-th equation in model 11 is given by

$$\begin{aligned} \mathbf{Y}_t &= (\mathbf{I}_2 - \bar{\mathbf{G}})^{-1} \left[\sum_{i=1}^{P} \bar{\mathbf{A}}_i \mathbf{Y}_{t-i} + \bar{\mathbf{a}} + \sum_{i=1}^{P} \bar{\mathbf{B}}_i \mathbf{X}_{t-i} + \sum_{i=0}^{P} \bar{\mathbf{C}}_i D_{t-i} Q_{t-i} + \bar{\mathbf{F}}_0 \ln T_t Q_t + \boldsymbol{\varepsilon}_t \right] \\ &\equiv \sum_{i=1}^{P} \mathbf{A}_i \mathbf{Y}_{t-i} + \mathbf{a} + \sum_{i=1}^{P} \mathbf{B}_i \mathbf{X}_{t-i} + \sum_{i=0}^{P} \mathbf{C}_i D_{t-i} Q_{t-i} + \mathbf{F}_0 \ln T_t Q_t + \mathbf{v}_t \end{aligned} \tag{15}$$

Where the disappearance of the accent above denotes a multiplication with $(\mathbf{I} - \mathbf{G})^{-1}$. For example

$$\mathbf{A}_i = \begin{bmatrix} \beta_i^r & \gamma_i^r \\ \beta_i^Q & \gamma_i^Q \end{bmatrix} \equiv (\mathbf{I}_2 - \mathbf{G})^{-1} \bar{\mathbf{A}}_i = \begin{bmatrix} \bar{\beta}_i^r + \bar{\gamma}_0^r \beta_i^Q & \bar{\gamma}_i^r + \bar{\gamma}_0^r \gamma_i^Q \\ \bar{\beta}_i^Q & \bar{\gamma}_i^Q \end{bmatrix} \tag{16}$$

The error term is $v_t \sim N(0, \Xi_v)$ where $\Xi_v = (\mathbf{I}_2 - \mathbf{G})^{-1} \Xi_\varepsilon (\mathbf{I}_2 - \mathbf{G})^{-1\prime}$. The model as such is not identified as we cannot track the structural parameters using its reduced form (15). This identification problem arises as the reduced model is not able to identify the $\bar{\gamma}_0^r$ parameter of the original model without some additional restrictions on the model. However, we can calculate its value from the relation $v_{1,t} = \varepsilon_{1,t} + \bar{\gamma}_0^r \varepsilon_{2,t}$ which implies

$$\bar{\gamma}_0^r = \frac{Cov\left(v_{1,t}, v_{2,t}\right)}{Var\left(v_{2,t}\right)} \tag{17}$$

The $\bar{\gamma}_0^r$ parameter can be interpreted as the instantaneous impact of an incoming trade on the return residual and therefore on return itself and must be larger than zero due to the bid-ask spread. Note that this contemporaneous correlation also implies that we cannot analyze the dynamics of the system by simply isolating a shock in the order flow innovation $\varepsilon_{2,t}$ as a shock in $\varepsilon_{2,t}$ tells us something about $\varepsilon_{1,t}$ and hence about the dynamics of the total system. However, Lütkepohl (1993) shows that the impulse response dynamics can still be calculated by simply multiplying both sides of equation (11) with the upper Choleski decomposition of the residuals variance-covariance matrix $\mathbf{\Xi}_v$. Because or model contains AR-terms, it is useful to rewrite model (15) compactly in its final form for estimation purposes

$$\begin{aligned} \mathbf{Y}_t &= \mathbf{A}\left(\mathbf{L}\right)^{-1}\left[\mathbf{a} + \mathbf{B}\left(\mathbf{L}\right)\mathbf{X}_t + \mathbf{C}\left(\mathbf{L}\right) D_t Q_t + \mathbf{F}_0 \ln T_t Q_t + \mathbf{v}_t\right] \\ &= \mathbf{Z}_t \mathbf{\Lambda} + \mathbf{u}_t \end{aligned} \tag{18}$$

where $\mathbf{Z}_t = \left(\boldsymbol{\iota}_2, \mathbf{X}_t, D_t Q_t, \ln T_t Q_t\right), \mathbf{\Lambda} = vec\left[\boldsymbol{\alpha}, \mathbf{\Phi}_1, \mathbf{\Phi}_2, \mathbf{\Phi}_3\right]$ and $\mathbf{u}_t = \mathbf{A}\left(\mathbf{L}\right)^{-1}\mathbf{v}_t$[30].The final form representation implies that $\mathbf{Y}_t | \mathbf{\Lambda}_t \sim N\left(\mathbf{Z}_t \mathbf{\Lambda}_t, \mathbf{A}\left(\mathbf{L}\right)^{-1} \mathbf{\Xi}_v \mathbf{A}\left(\mathbf{L}\right)^{-1\prime}\right)$ and we calculate the joint density of the endogenous variables using Maximum Likelihood. An illustration of this method is given in Hamilton (1994).

B Impulse Response Functions

We now turn to the details of the calculation of the impulse responses for the local trading platform. One way of constructing the impulse response function has been suggested by Hasbrouck (1991b). By making assumptions about invertability and covariance stationary components one can represent the VAR(p) model as an MA(∞) model. The coefficients of this MA model are then the quote revision parameters. In our case, we take as a starting point the reduced form model (15).

$$\begin{aligned} r_t &= \alpha^r + \sum_{i=1}^{P}\left(\beta_i^r + z_i^r \ln\frac{T_{t-i,\tau}}{\bar{T}_\tau}\right) r_{t-i} + \tau_0^r \ln\frac{T_{t,\tau}}{\bar{T}_\tau} Q_t + \sum_{i=1}^{P}\left(\gamma_1^r + \tau_i^r \ln\frac{T_{t-i,\tau}}{\bar{T}_\tau}\right) Q_{t-i} + v_{1,t} \\ Q_t &= \alpha^Q + \sum_{i=1}^{P}\left(\beta_i^Q + z_i^Q \ln\frac{T_{t-i,\tau}}{\bar{T}_\tau}\right) r_{t-i} + \sum_{i=1}^{P}\left(\gamma_i^Q + \tau_i^Q \ln\frac{T_{t-i,\tau}}{\bar{T}_\tau}\right) Q_{t-i} + v_{2,t} \end{aligned} \tag{19}$$

[30] The lag operators are defined as $\underset{(2\times2)}{\mathbf{A}\left(\mathbf{L}\right)} = \mathbf{I}_2 - \sum_{i=1}^{p} \mathbf{A}_i \mathbf{L}^i, \underset{(2\times2)}{\mathbf{B}\left(\mathbf{L}\right)} = \sum_{i=1}^{p} \mathbf{B}_i \mathbf{L}^i, \underset{(2\times2)}{\mathbf{C}\left(\mathbf{L}\right)} = \sum_{i=0}^{p} \mathbf{C}_i \mathbf{L}^i$ and $\mathbf{\Phi}_1 = \mathbf{A}\left(\mathbf{L}\right)^{-1}\mathbf{B}\left(\mathbf{L}\right), \mathbf{\Phi}_2 = \mathbf{A}\left(\mathbf{L}\right)^{-1}\mathbf{C}\left(\mathbf{L}\right)$ and $\mathbf{\Phi}_3 = \mathbf{A}\left(\mathbf{L}\right)^{-1}\mathbf{F}_0$.

We assume that the system at time $t = 0$ is in its long run equilibrium, i.e. no one is participating in trades ($Q_{t-i} = 0, i = 1, \ldots, P$) while market makers are not actively making the market ($r_{t-i} = 0, i = 1, \ldots, P$). The impulse response function of a time series r_t due to an unexpected shock in Q_t is given by I_R and is analyzed at time $t + n$ through the following expression

$$\begin{aligned} I_r\left(n, \varepsilon_{2,t} = \delta, \Omega_{t-1}\right) &= E\left[r_{t+n} | \varepsilon_{2,t} = \delta, \boldsymbol{\varepsilon}_{t+1} = \ldots = \boldsymbol{\varepsilon}_{t+n} = \mathbf{0}, \Omega_{t-1}\right] \\ & \quad -E\left[r_{t+n} | \varepsilon_{2,t} = 0, \boldsymbol{\varepsilon}_{t+1} = \ldots = \boldsymbol{\varepsilon}_{t+n} = \mathbf{0}, \Omega_{t-1}\right] \end{aligned} \tag{20}$$

Here the first term of (20) reflects the system when it has been hit only once by a shock δ at time t while the second term assumes that the system stays in its long run equilibrium. Because both terms are conditioned under the same information set Ω_{t-1}, it analyzes the realization of a system which are identical up to time t. An important aspect pointed out by Koop et al. (1996) is the fact that the impulse response function in linear models do not depend on the history of the information set. This aspect is worth considering in our model as one can expect a different impulse response function for r_t during different trading intensity. We therefore apply two methods for calculating the impulse response function as given by system (19).

The first method is by simply substituting the average trading duration for $T_{t-i,\tau}$ which is by definition exactly equal to $\bar{T}_\tau$. As a result, system (19) changes into a linear VAR(p) model.

$$\begin{aligned} r_t &= \sum_{i=1}^{P} \beta_i^r r_{t-i} + \sum_{i=1}^{P} \gamma_i^r Q_{t-i} + v_{1,t} \\ Q_t &= \sum_{i=1}^{P} \beta_i^Q r_{t-i} + \sum_{i=1}^{P} \gamma_i^Q Q_{t-i} + v_{2,t} \end{aligned} \tag{21}$$

The second method that we apply in here is to compare the price impact of an unexpected buy during periods of high and low trading intensity. We analyze the system under the situation that a trade is conducted just once in a period of high and low trading intensity. To do so, we the 10-th percentile trade based on the distribution of $\tau_{high} = [10.00 - 10.30)$ am interval and the 90-th trade based on the distribution of $\tau_{low} = [17.00 - 17.30)$pm interval. On average, these intervals have the highest and lowest number of trades. In other words, for every bond we select two trades with duration $T_{t-i,\tau}^{high}$ and $T_{t-i,\tau}^{low}$ such that

$$\begin{aligned} T_{t-i,\tau}^{high} &= 10th - \text{percentile trade in interval } \tau = \tau_{high} \\ T_{t-i,\tau}^{low} &= 90th - \text{percentile trade in interval } \tau = \tau_{low} \end{aligned} \tag{22}$$

As a result, the system changes again into a VAR(p) model

$$
\begin{aligned}
r_t &= \alpha^r + \sum_{i=1}^{P} \beta_i^r r_{t-i} + \tau_0^r \pi_0 Q_t + \sum_{i=1}^{P} \gamma_1^r Q_{t-i} + v_{1,t} \\
Q_t &= \alpha^Q + \sum_{i=1}^{P} \beta_i^Q r_{t-i} + \sum_{i=1}^{P} \gamma_i^Q Q_{t-i} + v_{2,t}
\end{aligned}
\tag{23}
$$

where π_0 is either $\ln \frac{T_{t-i,\tau}^{high}}{\bar{T}_\tau}$ or $\ln \frac{T_{t-i,\tau}^{low}}{\bar{T}_\tau}$.

Note that the dynamics of system (21) and (23) cannot be analyzed by simply isolating a shock in the order flow innovation $\varepsilon_{2,t}$. The reason for this is the contemporaneous correlation between the residuals. Hence, as a shock in $\varepsilon_{2,t}$ tells us something about $\varepsilon_{1,t}$ and hence about the dynamics of the total system. This is an important reason to use the MA(∞) model as the orthogonal innovations do not obscure the actual reaction towards the system. For example, both (21) and (23) can be written as $\mathbf{Y}_t = \boldsymbol{\varepsilon}_t + \sum_{i=1}^{\infty} \boldsymbol{\theta}_i \boldsymbol{\varepsilon}_{t-i}$ where the matrix $\boldsymbol{\theta}_n$ has the interpretation $\partial \mathbf{Y}_{t+n} = \boldsymbol{\theta}_n \partial \boldsymbol{\varepsilon}_t$. Instead of this MA($\infty$) approach, we continue to use the reduced form of system(19) and follow the approach of Lütkepohl (1994), page 51, which requires the use of a Choleski decomposition of the variance matrix.

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Tables Section

Table 1: Domestic government debt

Medium and long term government debt oustanding (billion EUR). *Source*:ECB: The EURO Bond Market.

Country	Debt	Average maturity
Austria	81	6.2
Belgium	173	6.1
France	573	6.2
Germany	599	6.8
Italy	885	6.1
Netherlands	169	6.3
Spain	225	5.5

Table 2: Minimum quantity of proposal

Round lots are executed automatically while odd lots are subject to the marketmakers acceptance. The minimum quantity proposal depends on the maturity of the security.

Market	**Minimum Quantity Proposals**	Orders	
		round lots	**odd lots**
MTS Amsterdam	5 - 10	2.5	0.5
MTS Austria	2.5 - 5	2.5	0.5
MTS Belgium	2.5 - 5 - 10	2.5	0.5
MTS France	2.5 - 5 - 10	2.5	0.5
MTS Germany	5 - 10	5	0.5
MTS Italy	2.5 - 5 - 10	2.5	0.5
MTS Spain	5 - 10	2.5	0.5
EuroMTS	2.5 - 5 - 10	2.5	0.5

Table 3: Number of MTS market participants

The first column shows the total number of participants on the local market. The second column shows the number of participants that have market making obligations while the third column shows the number of market makers which are both market maker on the local and EuroMTS market.

Market	Participants	Market Makers	Market makers (both markets)
MTS Amsterdam	31	22	21
MTS Belgium	28	19	19
MTS Finland	20	18	16
MTS France	31	31	30
MTS Germany	60	39	39
MTS Ireland	10	10	10
MTS Italy	140	38	33
MTS Portugal	23	19	17
MTS Spain	24	22	22
EuroMTS	95	79	

Table 4: Overview cash traded bonds

Description of our dataset in terms of trades and volume. The right part of the table shows the percentage of trades conducted on the EuroMTS and on the local platform and the overall average trading size. The Italian platform also offers trading facilities for German securities.

Market	**Type**	**Transactions**	**Volume**	**% EuroMTS Platform**	**% local platform**	**Average trade size**
Germany	DBR	14683	90033	56	37	6.1
	OBL	9703	81184	67	26	8.4
	BKO	7128	62385	72	28	8.8
	total	**31514**	**233602**			7.4
Italy	BTP	518432	2851689	17	83	5.5
	CTZ	43698	230281		100	5.3
	CCT	139615	692323.5		100	5.0
	BOT	27875	126218		100	4.5
	total	**729620**	**3900511.5**			5.3
France	AOT	33864	207018	41	59	6.1
	BTANS	29472	252045	55	45	8.6
	total	**63336**	**459063**			7.2
Belgium	OLO	43431	316857	22	78	7.3

Table 5: The number of trades in the EUR 2.5, 5 and 10 million buckets

Table shows us the percentage of total trades in the various quantity buckets. OLO, OAT, DBR and BTP bonds are long-term bonds and the central focus of our analysis. All other bonds have either a medium or short time to maturity.

		% 2.5mio	**% 5mio**	**%10 mio**	**total**
Italy	BTP	22	64	10	96
	CTZ	69	11	8	88
	CCT	66	10	9	85
	BOT	69	17	5	91
France	AOT	8	66	24	98
	BTANS	0	31	67	98
					0
Germany	DBR	3	75	19	97
	OBL	0	46	49	95
	BKO	0	39	57	96
Belgium	OLO	4	50	44	98

Table 6: Volume Weighted Quoted Spread for domestic and EuroMTS markets. Numbers shown are in percentage from midpoint of the best bid-ask price.

	Class A	Class B	Class C	Class D
Mts Italy				
Trade size	BTP 15/07/05	BTP 01/03/07	BTP 01/08/11	BTP 01/05/31
5	0.0199	0.0284	0.0270	0.1200
10	0.0230	0.0300	0.0291	0.1325
25	0.0288	0.0382	0.0350	0.1489
Mts France				
Trade size	BTAN 12/07/05	BTAN 12/07/06	OAT 25/10/11	OAT 25/10/32
5.0	0.0270	0.0252	0.0308	0.1255
10.0	0.0271	0.0256	0.0308	0.1373
25.0	0.0446	0.0300	0.0351	0.1554
Mts Germany				
Trade size	OBL 135 05/05	OBL 138 08/06	DBR 04/01/12	DBR 04/01/31
5	0.0307	0.0381	0.0330	0.1521
10	0.0343	0.0395	0.0354	0.1680
25	0.0393	0.0491	0.0397	0.1811
Mts Belgium				
Trade size	OLO 34 09/05	OLO 37 09/06	OLO3609/11	OLO 3103/28
5	0.0281	0.0299	0.0411	0.1407
10	0.0289	0.0300	0.0412	0.1504
25	0.0393	0.0339	0.0467	0.1657
Euromts: Italian government bonds				
Trade size	BTP 15/07/05	BTP 01/03/07	BTP 01/08/11	BTP 01/05/31
5	0.0225	0.0290	0.0280	0.1178
10	0.0245	0.0307	0.0300	0.1303
25	0.0292	0.0369	0.0363	0.1486
Euromts: French government bonds				
Trade size	BTAN 07/05	BTAN 12/07/06	OAT 25/10/11	OAT 25/10/32
5	0.0248	0.0248	0.0290	0.1249
10	0.0249	0.0254	0.0298	0.1380
25	0.0289	0.0310	0.0335	0.1576
Euromts: German government bond				
Trade size	OBL 135 05/05	OLB 138 08/06	DBR 04/01/12	DBR 04/01/31
5	0.0399	0.0380	0.0317	0.1523
10	0.0343	0.0400	0.0339	0.1626
25	0.0613	0.0495	0.0374	0.1784
Euromts: Belgian government bonds				
Trade size	OLO 37 09/05	OLO 3709/06	OLO36 09/11	OLO 31 03/28
5	0.0281	0.0299	0.0414	0.1386
10	0.0287	0.0299	0.0416	0.1482
25	0.0346	0.0344	0.0468	0.1648

Table 7: Effective and realized spreads for the domestic and EuroMTS markets. Table offers a comparison of the realized spread and the average effective spread. The effective spread is defined as the absolute difference between price and previous midquote. The realized spread is the difference between the price and subsequent midquote. The T-statistics reflects the outcome of testing whether there exist a significant difference between the spreads on the domestics trading platform versus EMTS.

Maturity	Bond	Domestic Effective	EMTS Effective	T-stat (eff.)	Domestic Realized	EMTS Realized	T-stat (real.)
	BTP 07/05	0.018	0.018	0.128	**0.000**	**0.005**	**3.544**
A	OBL 05/05	0.358	0.444	0.208	0.319	0.413	0.243
	BTNS 07/05	0.032	0.019	0.753	0.012	0.002	1.601
	OLO 10/04	0.010			0.013		
	BTP 03/07	0.026	0.029	0.634	0.003	0.006	0.108
B	OBL 08/06	0.033	0.021	1.028	**-0.002**	**0.026**	**2.207**
	BTNS 07/06	0.032	0.022	1.088	0.016	0.000	1.674
	OLO 09/06	0.034	0.035	0.046	0.008	0.014	0.731
	BTPS 08/11	0.038	0.041	0.674	0.004	-0.002	0.378
C	DBR 01/12	0.044	0.044	0.023	-0.022	0.005	1.630
	AOT 10/11	0.046	0.049	1.025	0.006	0.010	0.296
	OLO 09/11	0.041	0.060	1.376	0.016	0.017	0.015
	BTP 05/31	0.110	0.114	0.272	0.028	0.023	0.300
D	DBR 01/31	0.143	0.138	0.104	0.021	-0.005	0.870
	OAT 10/32	0.111	0.060	1.376	0.007	0.072	1.324
	OLO 03/28	0.108	0.113	0.221	-0.065	0.094	1.083

BTP are Italian bonds, BTNS and OAT are French, OBL and DBR are German, OLO are Belgian bonds. The Belgium October 2004 (OLO 10/04) is not traded on the EMTS platform.

Table 8: Spread for absolute price changes for domestic and EMTS trading platforms. This table shows spread estimates based on absolute price changes for class A, B, C and D benchmark bonds as a percentage of the price. We test Spread EMTS = spread domestic platform using a standard t-test. The numbers in bold face reflects significance at 5% level.

Class	A	B	C	D
	Btp 15/07/05	Btp 01/03/07	Btp 01/08/11	Btp 01/05/31
Euromts	**0.0335**	0.0550	**0.0496**	0.1326
Mts Italy	**0.0202**	0.0338	**0.0320**	0.0839
T-stat	**2.06**	1.68	**2.29**	1.18
	Btan 12/07/05	Btan 12/07/06	Oat 25/10/11	Oat 25/10/32
Euromts	**0.0434**	0.1038	0.0682	0.1754
Mts France	**0.0492**	0.0548	0.0758	0.3564
T-stat	**2.33**	1.20	0.45	1.61
	Obl 135 05/05	Obl 138 08/06	Dbr 04/01/12	Dbr 04/01/31
Euromts	0.0378	**0.0401**	0.1699	0.1789
Mts Germany	0.0309	**0.0376**	0.0916	0.1618
T-stat	0.79	**3.04**	0.53	1.44
	Olo 34 09/05	Olo 37 09/06	Olo 36 09/11	Olo 31 03/28
Euromts	0.0597	0.0439	0.0935	0.2631
Mts Belgium	0.0498	0.0560	0.0717	0.2827
T-stat	1.26	0.78	0.76	0.05

Table 9: Overview of 10-year sovereign bonds

Table shows us some trading characteristics of the bonds considered for our econometric analysis. We focus on the 10-year benchmark bonds of Belgium, France, Germany and Italy.

Bond Type	OLO 09/11	OAT 10/11	DBR 01/11	BTP 08/11
Total number of trades	5542	4754	2886	62735
Percentage EuroMTS trades	32	67	72	21
Total volume	48472	32028	17520	354140
Volume EuroMTS	14585	20875	12905	80758
Average local volume	8.99	7.11	5.71	5.52
Average EuroMTS volume	8.22	6.55	6.21	6.13
EuroMTS / local volume	0.91	0.92	1.09	1.11
percentage 5mio trades	27	67	81	88
percentage 10mio trades	71	32	17	9
Bond Type	OLO 09/12	OAT 04/12	DBR 01/12	BTP 02/12
Total number of trades	1670	526	1022	16382
Percentage EuroMTS trades	35	34	60	13
Total volume	15205	4692.5	5650	88450
Volume EuroMTS	5110	1630	3380	13663
Average local volume	9.3	8.8	5.6	5.2
Average EuroMTS volume	8.7	9.1	5.5	6.4
EuroMTS / local volume	0.94	1.03	0.99	1.22
percentage 5mio	21	21	89	81
percentage 10mio	78	78	10	9

Table 10: Glosten-Harris estimation results

Estimation output of the Glosten-Harris model. Specifically, we estimate the following equation using OLS:

$$\triangle P_t = \alpha + c_0 \left(I_t - I_{t-1}\right) + \delta^c \left(D_t I_t - D_{t-1} I_{t-1}\right) + a_1 I_t N_t + \delta^{\alpha} D_t N_t I_t + e_t \tag{24}$$

The c_0 and a_1 component reflects the level of fixed and variable costs in basispoints per EUR 1mio face value. The δ^c and δ^{α} component are dummy variables indicating 1 if a trade occurs on the EMTS platform. The standard errors are corrected for heteroskedasticity using White standard errors.

		α	c_0	δ^c	a_1	δ^{α}	R^2
OLO_11	coefficient	-0.013	**0.494**	0.810	0.016	-0.043	0.001
	s.e	0.223	**0.236**	0.621	0.041	0.056	
	t-stat	-0.060	**2.098**	1.304	0.398	-0.757	
OLO_12	coefficient	-0.124	**0.482**	0.192	0.003	0.002	0.005
	s.e	0.164	**0.235**	0.333	0.022	0.048	
	t-stat	-0.756	**2.047**	0.576	0.154	0.035	
OAT_11	coefficient	-0.028	0.279	-0.129	0.043	-0.015	0.001
	s.e	0.095	0.177	0.199	0.182	0.034	
	t-stat	-0.293	1.573	-0.648	0.239	-0.435	
OAT_12	coefficient	-0.210	0.671	-1.116	-0.021	0.053	0.003
	s.e	0.411	0.800	0.867	0.047	0.094	
	t-stat	-0.510	0.839	-1.287	-0.443	0.561	
DBR_11	coefficient	-0.052	0.188	**1.082**	**0.299**	-0.277	0.008
	s.e	0.195	0.427	**0.487**	**0.092**	0.111	
	t-stat	-0.268	0.442	**2.222**	**3.255**	-2.498	
DBR_12	coefficient	-0.177	0.672	0.092	0.091	-0.040	0.001
	s.e	0.274	0.498	0.581	0.121	0.136	
	t-stat	-0.645	1.351	0.159	0.752	-0.293	
BTP_11	coefficient	-0.009	**0.286**	**0.094**	**0.061**	**-0.033**	0.007
	s.e	0.008	**0.010**	**0.017**	**0.002**	**0.003**	
	t-stat	-1.161	**28.572**	**5.611**	**32.658**	**-10.105**	
BTP_12	coefficient	-0.040	**0.358**	0.043	**0.072**	**-0.045**	0.003
	s.e	0.022	**0.027**	0.053	**0.005**	**0.008**	
	t-stat	-1.804	**13.483**	0.804	**15.865**	**-5.460**	

Table 11: Dufour-Engle estimates for the BTP 2011 bond

Estimation of the Engle-Dufour model using Maximum likelihood. The standard errors are corrected for heteroskedasticity using White standard errors. The γ_0 coefficient is calculated using the correlation between the error terms. The left-hand side shows the estimation results for the return equation and the right-hand side shows the estimation result for the quantity equation.

Parameters	Coefficient	White S.E	t-stat	Coefficient	White S.E	t-stat
	return equation BTP 2011			**Signed Quantity equation BTP 2011**		
β_1	-0.04200	0.01697	**-2.47451**	0.00169	0.01528	0.11036
β_2	0.01043	0.01071	0.97390	-0.04876	0.01530	**-3.18679**
β_3	-0.00765	0.00822	-0.92993	-0.06047	0.01517	**-3.98730**
γ_0	0.113					
γ_1	0.00206	0.00232	0.89017	0.26106	0.00483	**54.06128**
γ_2	0.00447	0.00216	**2.06620**	0.06278	0.00502	**12.51208**
γ_3	0.00347	0.00190	1.83051	0.04636	0.00490	**9.46441**
z_1	0.00573	0.01145	0.50029	0.02331	0.01070	**2.17844**
z_2	-0.01628	0.00886	-1.83687	0.03130	0.01081	**2.89564**
z_3	0.01225	0.00726	1.68867	0.04381	0.01076	**4.07265**
τ_0	0.04616	0.00300	**15.39971**			
τ_1	-0.00599	0.00259	**-2.31135**	-0.04161	0.00487	**-8.54999**
τ_2	-0.00291	0.00253	-1.15059	-0.04255	0.00488	**-8.72268**
τ_3	-0.00418	0.00223	-1.87480	-0.03278	0.00476	**-6.89203**
δ_0	-0.02452	0.00262	**-9.37369**			
δ_1	-0.00365	0.00248	-1.47361	0.01688	0.00869	**1.94345**
δ_2	0.00181	0.00286	0.63456	0.02826	0.00869	**3.25090**
δ_3	0.00480	0.00273	1.75676	0.03633	0.00869	**4.18295**
α	-0.00471	0.00837	-0.56235	0.08477	0.02333	3.63400

Table 12: Wald test for duration effects

Wald test for the joint hypothesis $\tau_0 = \tau_1 = \tau_2 = \tau_3 = 0$. Under the nullhypothesis this variable is $\chi_{(4)}$ distributed.

	Wald-statistic		Wald-statistic
OLO_11	13.53	OLO_12	5.92
OAT _11	20.20	OAT_12	1.02
DBR_11	3.16	DBR_12	2.48
BTP_11	242.03	BTP_12	54.86

Graphs Section

Figure 1: Spread between the Italian 10-year benchmark bond (BTP) versus the 10-year German Bund. The data of weekly observations runs from March 1991 until December 2002. *Source: Thomson Financials*

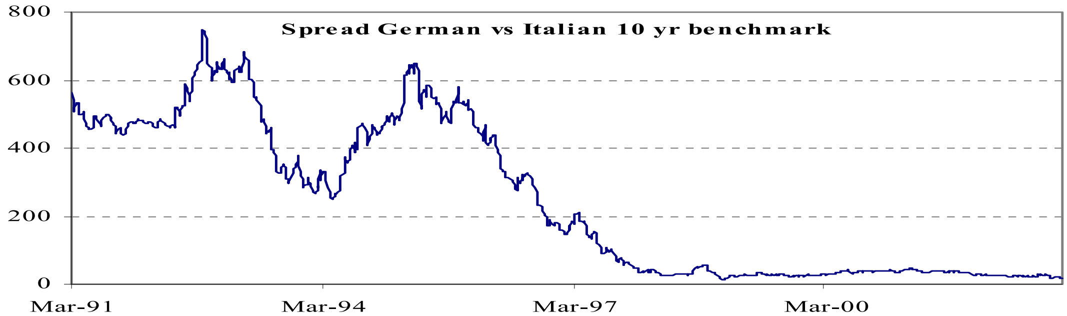


Figure 2: The estimated spread based on Absolute Price differences on the MTS versus the EMTS. Data runs from 4 February 2002 until 15 February 2002.

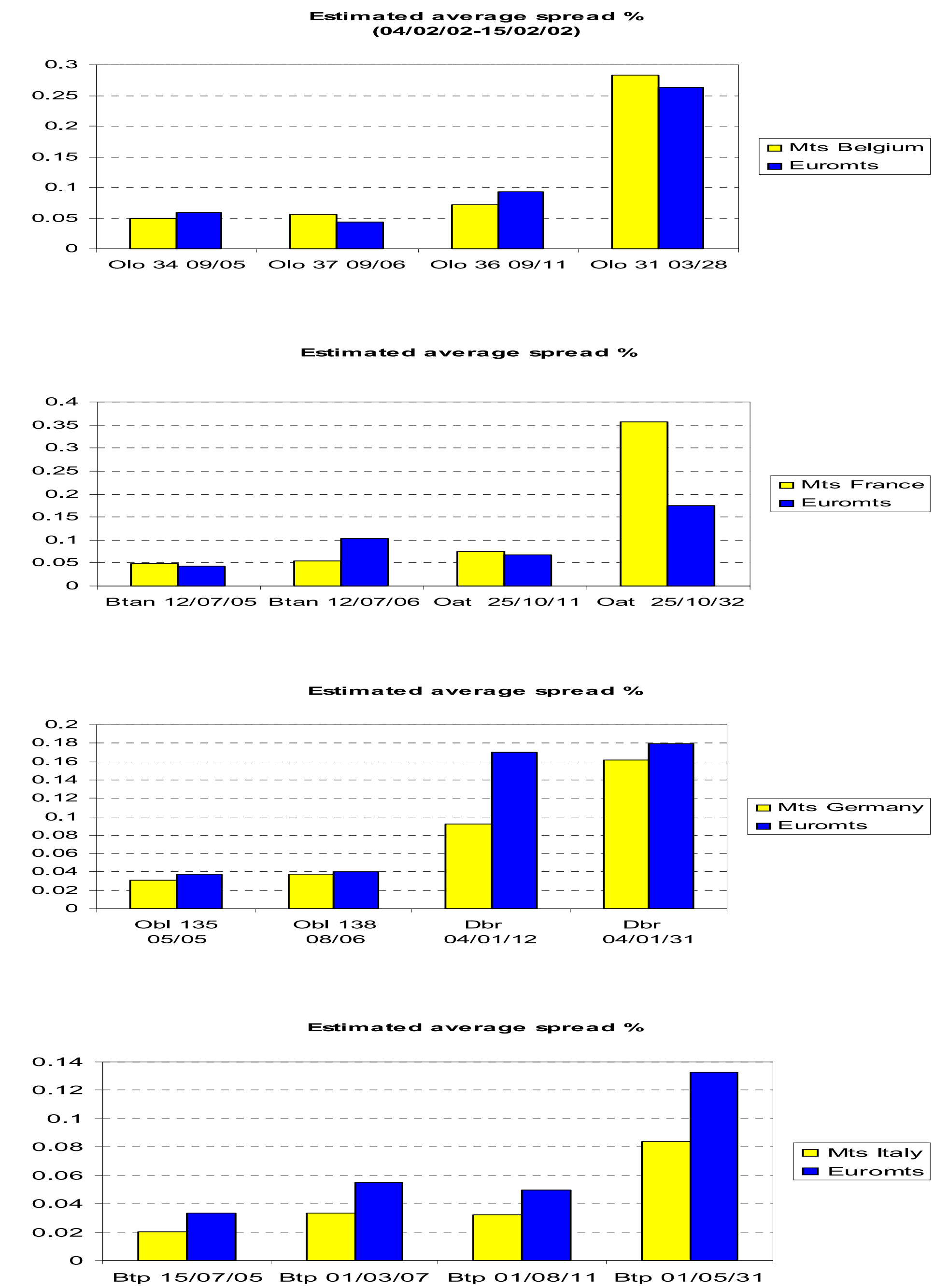


Figure 3: Intraday pattern of quoted spread for the BTP 2011.

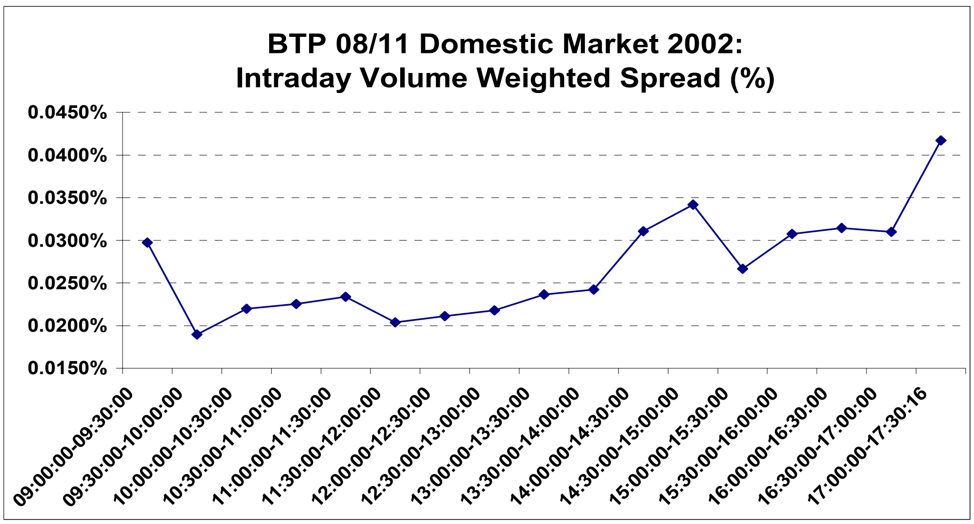
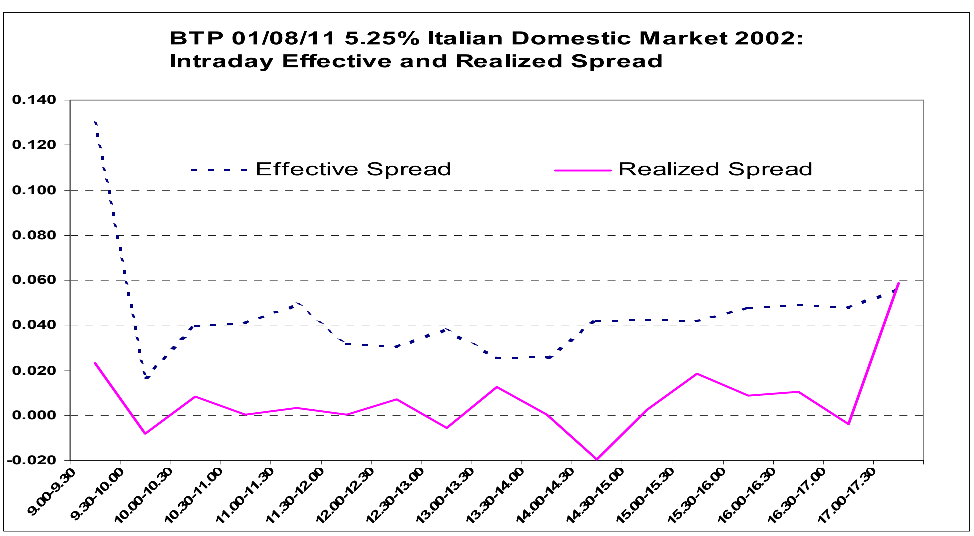


Figure 4: The average effective and realized spread.



Impulse Response Functions

The impulse response functions for the Italian 2011 and 2012 bonds using average trading intensity $T_{t-i,\tau}= \bar{T}_\tau$ are given in figure 5 and 6. By using the average duration, system (19) changes into a linear VAR(p) model. Specifically, the impulse response of the following system is analyzed:

$r_t = \alpha^r + \sum_{i=1}^{P} \beta_i^r r_{t-i} + \sum_{i=1}^{P} \gamma_i^r Q_{t-i} + v_{1,t}$
$Q_t = \alpha^Q + \sum_{i=1}^{P} \beta_i^Q r_{t-i} + \sum_{i=1}^{P} \gamma_i^Q Q_{t-i} + v_{2,t}$

The figures also show the impulse response functions for the securities using a fixed maximum and minimum trading intensity $T_{t-i,\tau}= \bar{T}_\tau$, system (19) changes into a linear VAR(p) model. Specifically, if taking time into account, we calculate the impulse response of the following system:

$$
\begin{aligned}
r_t &= \alpha^r + \sum_{i=1}^{P} \beta_i^r r_{t-i} + \tau_0^r \pi_0 Q_t + \sum_{i=1}^{P} \gamma_1^r Q_{t-i} + v_{1,t} \\
Q_t &= \alpha^Q + \sum_{i=1}^{P} \beta_i^Q r_{t-i} + \sum_{i=1}^{P} \gamma_i^Q Q_{t-i} + v_{2,t}
\end{aligned}
$$

where π_0 is either $\ln \frac{T_{t-i,\tau}^{high}}{\bar{T}_\tau}$ or $\ln \frac{T_{t-i,\tau}^{low}}{\bar{T}_\tau}$.

We calculate the response function of return given an unexpected buy trade at $t = 0$ of EUR five million. The lower graph shows the accumulated response of return.

Figure 5: Italian 2011 bond

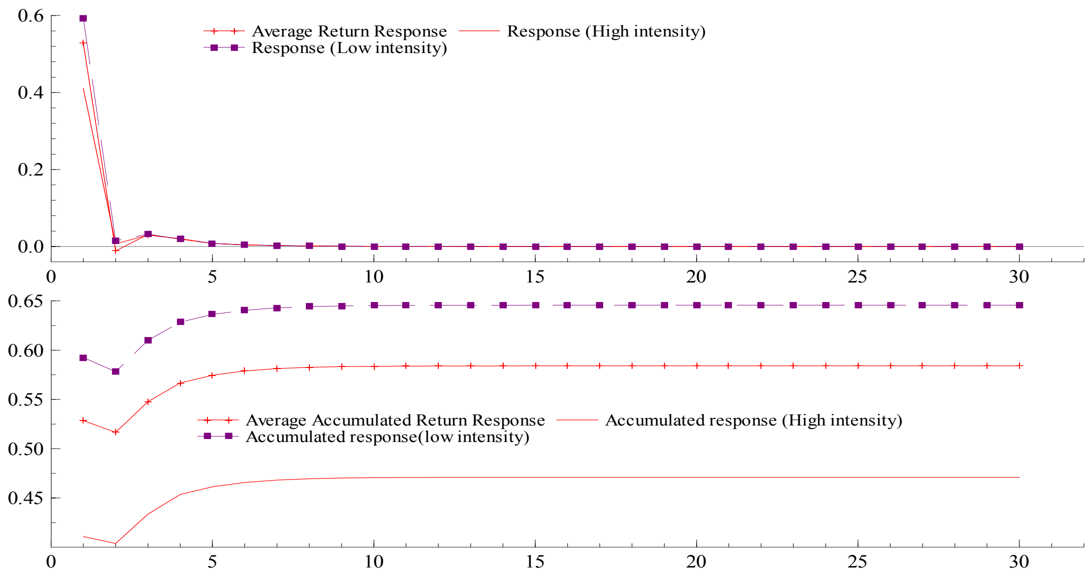


Figure 6: Italian 2012 bond