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Essays on European bond markets

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Chapter 3

Trading European Sovereign Bonds

Abstract

Using a unique dataset on the MTS Global Market bond trading system, we study a variety of spread measures for different classes of bond maturities from different countries. The quoted and effective spread are related to maturity and trading intensity. Eurozone securities can be traded on a domestic and European (or EuroMTS) platform. Despite this fragmentation, the markets are closely connected in terms of liquidity. We also estimate the price impact of order flow and control for the intraday trading intensity and the announcement of macroeconomic news. The regression results show a larger impact of order flows during announcement days and a positive relation between trading intensity and price impact. We relate these findings to interdealer trading and to the structure of European bond markets.

3.1 Introduction and Motivation

This chapter focuses on the trading activity of the Eurozone bond market. 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 interdealer trading is frequently being observed. Due to its obvious importance, empirical research on the microstructure of bond markets has increased in recent years.\(^1\) In this paper we study the microstructure of the MTS Global Market system, which is the most important European interdealer fixed income trading system.\(^2\) This system is composed of a number of trading platforms on which designated bonds can be traded. The trading system is fully automated and effectively works as an electronic limit order market.\(^3\) There are a few interesting features of this trading platform.

The first interesting feature of the MTS trading platform is its organizational setup. Fixed income securities can be traded on a domestic and an European (EuroMTS) platform. The range of securities being traded on the domestic platform is

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\(^2\)According to the Financial times (January 5, 2005), more than 50 percent of the Eurozone government bond trading is handled by EuroMTS.

\(^3\)The structure of the MTS trading platforms are very similar to the EBS and D2002 electronic trading system for the foreign exchange market, but different from the quote screen-based US Treasury bond trading system. The European bond market contains however a much richer menu of bonds than the US market. Although the European capital market has integrated considerably in the last number of years, mainly through the introduction of a single currency. European bonds can still differ in their credit rating. This varies from AA2 for Italy to AAA for Austrian, Dutch, French and German bonds (based on Moody’s credit rating).
3.1. INTRODUCTION

however much larger than on the EuroMTS trading platform. A dealer on the domestic trading platform can therefore trade a much wider range of bonds. However, the existence of both trading platforms suggests differences and we therefore ask ourselves the following question: Why would a market maker with entrance to the local platforms also operate on the EuroMTS trading platform? To answer this question, a detailed study on the costs and the dynamics of price formation is needed. Throughout the paper, we provide a comparison of the trading costs and price dynamics on the domestic MTS markets and the EuroMTS by calculating comparative measures of liquidity, such as the quoted and effective spread. We show that despite the apparent fragmentation of trading on domestic platforms and EuroMTS, the markets are closely connected in terms of liquidity.

The second interesting feature of the MTS Global Market system is its pure interdealer platform. This allows us to study the price and order flow dynamics under competitive market making. We ask ourselves: What are the dynamics of prices in the Eurozone fixed income market under competitive market making and interdealer trading? What is the role of trading intensity? Interestingly, the study of trading intensity and its relation to price and order flow dynamics do not explicitly take the role of interdealer trading into consideration. Single dealer models like Kyle (1985) and Easley and O'Hara (1992) argue that there exist a positive relation between information and trading intensity as more informed traders are active during large market activity. This means that any unexpected trade during active trading has a higher impact on prices. Empirical results by Dufour and Engle (2000) and Spierdijk (2002) indeed suggests that a higher trading intensity is related to a stronger price impact of trades. On the other hand, Diamond and Verrechia (1987) argue that short sale constraints will lead to a delay of bad news as informed traders are constrained from short selling. The expected price impact of trades arriving after a longer period

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

We think that interdealer trading may shed a different light on these results. Manaster and Mann (1996), Hansch, Naik and Viswanathan (1998) and Reiss and Werner (1998) show that dealers use interdealer trading to control their inventory position. However, Ho and Stoll (1983) shows that interdealer trading is more costly compared to outside customer trading because dealers have to pay a fee (to the other dealer) rather than receiving a fee (from an outside customer). In addition, Garman (1976) shows that there is less need to adjust the spread as traders enter the market on a frequent basis, which by definition occur during high market activity. Next to these searching costs, interdealer trading can also result in a repeated passing of inventory among dealers as they have the moral obligation to quote prices. Lyons (1997) calls this repeated passing of inventory 'hot-potato" trading and he shows that this creates noise in the pricing process when dealers are risk averse and speculative. In other words, a dealer's decision to conduct an interdealer trade depends on his ability to offset his inventory using customer order flow. Not only is this cheaper compared to interdealer trading; it also avoids the "hot-potato" process. This means that the price impact of a trade is much larger during periods where trading intensity is low because customer flows are scarce. Our data provides an opportunity to test this.

It is important to notice that our rationale in predicting price movements through order flow is built on inventory control and the costs associated with interdealer trading. However, market circumstances may create urgency to trade and if this urgency becomes the dominant factor, our arguments become invalid. Fleming and Remolona (1999), Balduzzi, Elton and Green (2001) and Cohen and Shin (2003) show that the largest price movements in government bond markets arise after the announcement of macroeconomic news. We therefore take this announcement effect into account. Green (2004) and Fleming (2001) documented a higher adverse selection component in government bond markets after the announcement of macroeconomic news due to stronger trading activity. This resulted in an increased information asymmetry. Cao
and Lyons (1999) and Lyons (2001) also found the same pattern for foreign exchange markets. Because trading intensity is typically high during these periods, one can argue that prices become more sensitive to trading intensity because the urgency to trade is more important than the interdealer costs. However, even during announcement days, we can distinguish between periods with active and less active trading. Green (2004) for example states that after the announcement "market participants actively watch trading to help determine the effect of economic news." Hence, the more trading activity, the better signal the dealer receives with respect to the true impact of economic news.

We document the following: order flows are strongly correlated but the correlation gradually decreases over time. We also find that the impact of a trade in a relative low trading intensive environment has a larger impact on price than in a relative high trading intensive environment. This contrast the findings of Dufour and Engle (2000) and Spierdijk (2002) for stock markets but confirms the dealers preference to trade with outside customers rather than the more costly interdealer trading. When we take announcement effects into consideration, we find the overall price sensitivity to order flow being stronger and this reflects the information asymmetry in order flow. However, this price sensitivity is magnified when trading activity is relative low. The latter confirms the important role of order flows to determine the true impact of economic news.

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 quoted and effective bid-ask spreads. Section 4 analyzes the impact of order flows and trading intensity on price discovery in the domestic and EuroMTS platforms for some important 10-year benchmark bonds. We estimate the model (i) using the full dataset and (ii) separating the dataset into days with and without macro-economic news announcements. Section 5 concludes the paper.
3.2 Market Description 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 2 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 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.

3.2.1 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 focus on bonds with a 10-year maturity in this paper, there exist a very active market for debt instruments with 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 Eurozone 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 Eurozone bond market is relative heterogeneous compared to for example the Eurozone money market. Table 3.1 shows the size of outstanding medium and long-term debt which differs considerably across countries. Also, despite the differences in issue size, governments choose to finance their needs using debt paper with almost

\footnote{Hartmann et al. (2001) provides an overview of the EU money market.}
Table 3.1: Medium and Long-Term Government Debt

Total amount and average maturity of medium and long-term government debt outstanding as of January 2002 in billions of Euro’s.

<table>
<thead>
<tr>
<th>Country</th>
<th>Debt (billions Euro’s)</th>
<th>Average maturity (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>81</td>
<td>6.2</td>
</tr>
<tr>
<td>Belgium</td>
<td>173</td>
<td>6.1</td>
</tr>
<tr>
<td>France</td>
<td>573</td>
<td>6.2</td>
</tr>
<tr>
<td>Germany</td>
<td>599</td>
<td>6.8</td>
</tr>
<tr>
<td>Italy</td>
<td>885</td>
<td>6.1</td>
</tr>
<tr>
<td>Netherlands</td>
<td>169</td>
<td>6.3</td>
</tr>
<tr>
<td>Spain</td>
<td>225</td>
<td>5.5</td>
</tr>
</tbody>
</table>

similar maturities. We now describe the bond market for German and Italian debt securities in more detail. We pick these two markets because both are highly liquid while having different credit ratings.6

**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 bond market has been given a strong boost since the unification of the two German states because 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. 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 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. These securities 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

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6In 2003, the German securities were rated ‘AAA’ while the Italian securities were rated with the ‘AA2’ status.
authority 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. 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 had its influence on the performance of Italian securities. The most important medium and long-term bond issued by the Italian treasury are BTPs (Buoni del Tesoro Poli-

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

8 In March 1997, the 10-year yield spread between Italian and German bonds was on average 180 basis points. By 2000, this spread was reduced to 40 basis points.
ennali). 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. 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, the same method also used 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.

3.2.2 The MTS System

Let us now turn our attention to the secondary market of the Eurozone. There are two ways in which bonds can be traded in the secondary market. The traditional way is through an organized exchange where 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. This system turned out to be successful by gaining a considerable market share since its creation in 1988 by the Bank of Italy and the Italian Treasury. Nowadays a private company manages MTS. The MTS system is an interdealer platform and therefore not accessible to individuals. A recent quarterly bulletin by the Italian treasury 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.

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

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9Source: Quarterly bulletin (third quarter 2002).
as an over-the-counter market. In order to improve market depth and activity, MTS was reformed in 1994 and this 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 in a number of other Eurozone countries. 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 final stage of development of the MTS platform was the creation of MTS Credit in May 2000 where only non-government bonds are traded. 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 assigned bonds in a two-way proposal for at least five hours a day. Table 3.2 gives us an overview of the total number of participants and the number of market makers. Table also shows, between brackets, the number of market makers who are active on both the domestic and EuroMTS platform.

As we can see, the largest parts 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. The large numbers of market

\[^{11}\text{MTS is operational in Finland, Ireland, Belgium, Amsterdam, Germany, France, MTS Portugal and Spain.}\]

\[^{12}\text{Financial institutions who are designated as market makers must fulfill some financial require-}\]
3.2. MARKET DESCRIPTION

Table 3.2: Number of Participants

The second column shows the total number of participants on the domestic trading platforms. The third column shows the number of domestic market makers. The number in brackets are the number of market makers who are also active on the EuroMTS system. The last row shows the the total number of participants on the EuroMTS is 95 from which 79 are dealers.

<table>
<thead>
<tr>
<th>Market</th>
<th>Participants</th>
<th>Market Makers (EuroMTS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MTS Amsterdam</td>
<td>31</td>
<td>22 (21)</td>
</tr>
<tr>
<td>MTS Belgium</td>
<td>28</td>
<td>19 (19)</td>
</tr>
<tr>
<td>MTS Finland</td>
<td>20</td>
<td>18 (16)</td>
</tr>
<tr>
<td>MTS France</td>
<td>31</td>
<td>31 (30)</td>
</tr>
<tr>
<td>MTS Germany</td>
<td>60</td>
<td>39 (39)</td>
</tr>
<tr>
<td>MTS Ireland</td>
<td>10</td>
<td>10 (10)</td>
</tr>
<tr>
<td>MTS Italy</td>
<td>140</td>
<td>38 (33)</td>
</tr>
<tr>
<td>MTS Portugal</td>
<td>23</td>
<td>19 (17)</td>
</tr>
<tr>
<td>MTS Spain</td>
<td>24</td>
<td>22 (22)</td>
</tr>
<tr>
<td>EuroMTS</td>
<td>95</td>
<td>79</td>
</tr>
</tbody>
</table>

makers active on both trading platforms suggest no competitive advantages in terms of quoting rights. In the early years, the system knew full transparency, but in 1997 anonymity was introduced in order to avoid “free-riding”.\(^{13}\) The maximum spread of these securities is 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 exists and is pre-specified depending on the liquidity and maturity of the security.\(^{14}\) Orders in round lots are executed automatically according to price specifications which differs among the platforms. For example, market makers for Belgian securities must have assets of at least 250 million Euro’s. For the EuroMTS, market makers must have assets of minimum net worth of 375 million Euro’s.

\(^{13}\)Massa and Simonov (2001b) showed, by analyzing MTS data before and after anonymity was introduced, that “free-riding” existed as the reputation of a market maker had impact on the price process.

\(^{14}\)The longer the maturity the higher the spread. The maximum spread is not binding. A market maker is allowed to propose a quotation larger than this maximum spread. However, activities
priority and the time that they are sent (first in first out). Odd lots are subject to the market makers' acceptance. No obligations apply to market takers (they can only buy or sell at given prices). 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 show the following functions:

- **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 so far.

Remember that all trades are anonymous and the identity of the counterpart is only revealed after a trade is executed for clearing and settlement purposes. Every market maker can post the entire quantity that he is willing to trade (block quantity) based on these trades are not added to his performance record.
3.2. MARKET DESCRIPTION

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 50 million Euro’s in a market where the minimum quantity is 10 million Euro’s can construct 5 drip quantities of 10 million Euro’s. 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’s. The MTS trading mechanism consist of two trading platforms where 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 a European system (EuroMTS). The latter platform offers trading only 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. 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.

3.2.3 Dataset

Our dataset 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 3.3 shows us the volume in the various markets including the number of transactions.

A total of 867,901 trades took place reflecting more than 4.9 trillion Euro’s of market value. The Italian bond market is by any means the largest market in

\[15\] As of January 2003.
Table 3.3: Overview Cash Traded Bonds

Trading characteristics of dataset. Table shows the percentage of trades on the EuroMTS and the local platform. ATS stands for average trading size (both platforms). The Italian platform also offers trading facilities for German securities. The right part of the table shows the percentage of total trades in the 2.5, 5.0 and 10 million Euro's buckets. OLO, OAT, DBR and BTP bonds are long-term bonds and the central focus of our analysis. Other bonds have either a medium or short time to maturity.

<table>
<thead>
<tr>
<th>Market</th>
<th>Transactions</th>
<th>Volume (millions)</th>
<th>% EuroMTS (local)</th>
<th>ATS</th>
<th>% Round lot trades 2.5</th>
<th>5</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DBR</td>
<td>14683</td>
<td>90033</td>
<td>56 (37)</td>
<td>6.1</td>
<td>3</td>
<td>75</td>
<td>19</td>
</tr>
<tr>
<td>OHL</td>
<td>9703</td>
<td>81184</td>
<td>67 (26)</td>
<td>8.4</td>
<td>0</td>
<td>46</td>
<td>49</td>
</tr>
<tr>
<td>BK0</td>
<td>7128</td>
<td>62385</td>
<td>72 (28)</td>
<td>8.8</td>
<td>0</td>
<td>36</td>
<td>57</td>
</tr>
<tr>
<td>Total</td>
<td>31514</td>
<td>233602</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Italy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BTP</td>
<td>518432</td>
<td>2851689</td>
<td>17 (83)</td>
<td>5.5</td>
<td>22</td>
<td>64</td>
<td>10</td>
</tr>
<tr>
<td>CTZ</td>
<td>43698</td>
<td>230281</td>
<td>0 (100)</td>
<td>5.3</td>
<td>69</td>
<td>11</td>
<td>8</td>
</tr>
<tr>
<td>CCT</td>
<td>139615</td>
<td>692324</td>
<td>0 (100)</td>
<td>5</td>
<td>66</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>BOT</td>
<td>27875</td>
<td>126218</td>
<td>0 (100)</td>
<td>4.5</td>
<td>69</td>
<td>17</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>729620</td>
<td>3900512</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>France</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OAT</td>
<td>33864</td>
<td>207018</td>
<td>41 (59)</td>
<td>6.1</td>
<td>8</td>
<td>66</td>
<td>24</td>
</tr>
<tr>
<td>BTNS</td>
<td>29472</td>
<td>252045</td>
<td>55 (45)</td>
<td>8.6</td>
<td>0</td>
<td>31</td>
<td>67</td>
</tr>
<tr>
<td>Total</td>
<td>63336</td>
<td>459063</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Belgium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OLO</td>
<td>43431</td>
<td>316857</td>
<td>22 (78)</td>
<td>7.3</td>
<td>4</td>
<td>50</td>
<td>44</td>
</tr>
</tbody>
</table>

our dataset as some 83% of all transactions come from this market. 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 460 billion and 233 billion Euro respectively.\(^{16}\) Although the German market is accepted as the benchmark

\(^{16}\)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.
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 800 billion Euro’s on a daily basis. The last bond market that we study is Belgium with a trading volume of 316 billion Euro’s. The most important bond of the Belgian treasury are linear bonds, or OLO’s as they are known after their combined acronym in French and Dutch (Obligations Linéaire-Lineaire Obligations). These are straight non-callable bonds with fixed coupon and redemption value. Table 3.3 also 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. The average trading size in Belgian, French and German long-term securities are quite comparable with more than 7 million Euro’s per trade while the average trading size in Italian securities stands at 5.3 million Euro’s. Because of the requirements with respect to the minimum lots being traded we counted the number of 2.5, 5 and 10 million Euro trades. More than 95 percent of all trades are either within the 2.5, 5 or 10 million Euro bucket with the exception of the Italian securities, where there is a relative large fraction of odd-lot trades. The most important reason for this difference is the relative small size of the

17 Source Eurex website. Every bond futures contract requires delivery of EUR 100,000 face value of a bond with maturity between 8.5 and 10.5 years at the moment of delivery.
participants on the domestic Italian platform. Now we are ready to calculate some different measures of spread on both the EuroMTS and the local trading platforms. If there are any differences in trading costs between both markets, this may justify the existence of the EuroMTS trading platform.

### 3.3 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, Irvine and Kandel (2000) suggested for gauging the ex-ante committed liquidity of a stock market organized like a limit order book. Denote the price schedule of bid and ask prices for all prices in the limit order book by $\mathbf{B} = \{B_h < B_{h-1} < \ldots < B_0\}$ and $\mathbf{A} = \{A_0 < A_{h-1} < A_h < \ldots\}$ respectively and let the corresponding amount of bonds offered or requested at these prices be given by $Q^z_h$ with $z = \{\text{bid, ask}\}$. Hence, $B_0$ and $A_0$ are the inside bid and ask prices with associated quantity of $Q^B_0$ and $Q^A_0$ respectively. Given a trading size $L$ of 5, 10, 25 million Euro, we can define an liquidity indicator $I^z_h$ as:

$$
I^z_h = \begin{cases} 
0 & \text{if } L \leq \sum_{i=1}^{h-1} Q^z_i \\
Q^z_h \left( L - \sum_{i=1}^{h} Q^z_i \right) & \text{if } \sum_{i=1}^{h-1} Q^z_i < L \leq \sum_{i=1}^{h} Q^z_i \\
1 & \text{if } L > \sum_{i=1}^{h} Q^z_i
\end{cases}
$$

(3.1)

Expressions (3.1) tell us that a market is least liquid if the trading size $L$ is larger than aggregated demand or supply up to price $h$ in the limit order book. As a result, an order cannot be filled at price $h$ and the liquidity indicator is therefore $I^z_h = 1$. In the most liquid market however, a trading size $L$ will be filled at the inside spread and therefore $I^z_h = 0$. The associated volume weighted quoted spread
Table 3.4: Volume Weighted Quoted Spread for domestic and EuroMTS platform.

Volume weighted quoted spread (VWQS) in cents for different classes of maturity from benchmark bonds of Belgium, France, Germany and Italy. Class A bonds have the lowest maturity while class D bonds have the highest maturity. Values in parenthesis are the volume weighted quoted spreads for the same bonds on the EuroMTS platform.

<table>
<thead>
<tr>
<th>Class</th>
<th>Mts Italy (EuroMTS Italy)</th>
<th>Mts France (EuroMTS France)</th>
<th>Mts Germany (EuroMTS Germany)</th>
<th>Mts Belgium (EuroMTS Belgium)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Trade size</td>
<td>BTP 15/07/05</td>
<td>BTP 01/03/07</td>
<td>BTP 01/08/11</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>1.99 (2.25)</td>
<td>2.84 (2.90)</td>
<td>2.70 (2.80)</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>2.30 (2.45)</td>
<td>3.00 (3.07)</td>
<td>2.91 (3.00)</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>2.88 (2.92)</td>
<td>3.82 (3.69)</td>
<td>3.50 (3.63)</td>
</tr>
</tbody>
</table>

Given a trading size $L$ is

$$2 \times \left[ \sum_{h=0}^{\infty} \frac{I_h^{ask} A_h Q_h^{ask} - \sum_{h=0}^{\infty} I_h^{bid} B_h Q_h^{bid}}{L (A_0 + B_0)} \right] \quad (3.2)$$

Table 3.4 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.\textsuperscript{18} We find that the quoted spread is similar across countries and for class A and B bonds, around 2 or 3 cents from the best prevailing mid-

\textsuperscript{18} The estimates are based on data from 4-8 and 11-15 February 2002.
quote. 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 bonds. The quoted spread is substantially higher for the longest maturity bucket D (13.5 to 30 years), ranging from 11 to 18 cents, 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. 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 cents, for a large trade of 25 million the quoted spread is still below 4 cents. This pattern is similar for the other bond classes and countries. In practice, trades larger than 10 million Euro's 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.

The volume weighted quoted spread includes periods where there is little trading and this gives an inaccurate indication of the actual trading costs. In addition, this measure does not take negotiations between traders into account. 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-ask quotes

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

(3.3)

where $p_t$ is the transaction price, $m_t$ the prevailing mid-quote 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).\footnote{In our dataset, we do not always observe $p_t$ and $m_t$ exactly at the same time and we select the previous mid-quote that is closest to the time of the transaction.} The realized spread compares the transaction price $p_t$ and the subsequent mid-quote, $m_{t-1}$ closest to the time $t$ transaction. Here we
3.3. LIQUIDITY ON THE MTS MARKET

Table 3.5: Effective and Realized spreads

Table offers a comparison of the realized spread and the average effective spread in cents. The T-statistics tests $\text{Spread}_{\text{EMTS}} = \text{Spread}_{\text{domestic}}$. BTP are Italian bonds, BTNS and OAT are French, OBL and DBR are German, OLO are Belgian bonds. At the moment of our analysis, the OLO 10/04 was not traded on the EuroMTS platform.

<table>
<thead>
<tr>
<th>Class</th>
<th>Bond</th>
<th>Effective Spread</th>
<th>Realized Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Domestic</td>
<td>EuroMTS</td>
</tr>
<tr>
<td>A</td>
<td>BTP 07/05</td>
<td>1.80</td>
<td>1.80</td>
</tr>
<tr>
<td></td>
<td>OBL 05/05</td>
<td>35.8</td>
<td>44.40</td>
</tr>
<tr>
<td></td>
<td>BTNS 07/05</td>
<td>3.20</td>
<td>1.90</td>
</tr>
<tr>
<td></td>
<td>OLO 10/04</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>BTP 03/07</td>
<td>2.60</td>
<td>2.90</td>
</tr>
<tr>
<td></td>
<td>OBL 08/06</td>
<td>3.30</td>
<td>2.10</td>
</tr>
<tr>
<td></td>
<td>BTNS 07/06</td>
<td>3.20</td>
<td>2.20</td>
</tr>
<tr>
<td></td>
<td>OLO 09/06</td>
<td>3.40</td>
<td>3.50</td>
</tr>
<tr>
<td>C</td>
<td>BTPS 08/11</td>
<td>3.80</td>
<td>4.10</td>
</tr>
<tr>
<td></td>
<td>DBR 01/12</td>
<td>4.40</td>
<td>4.40</td>
</tr>
<tr>
<td></td>
<td>AOT 10/11</td>
<td>4.60</td>
<td>4.90</td>
</tr>
<tr>
<td></td>
<td>OLO 09/11</td>
<td>4.10</td>
<td>6.00</td>
</tr>
<tr>
<td>D</td>
<td>BTP 05/31</td>
<td>11.00</td>
<td>11.4</td>
</tr>
<tr>
<td></td>
<td>DBR 01/31</td>
<td>14.30</td>
<td>13.80</td>
</tr>
<tr>
<td></td>
<td>OAT 10/32</td>
<td>11.10</td>
<td>6.00</td>
</tr>
</tbody>
</table>

use a similar definition,

$$\hat{\text{S}}_{\text{realized}} = \frac{1}{T} \sum_{t=1}^{T} 2I_t(p_t - m_{t-1}) \quad (3.4)$$

It is obviously not always the case that the trade price is above/below the subsequent mid-quote for buyer/seller initiated trades, as the market may have moved. Therefore, the realized spread measure may be negative. Table 3.5 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 trades and mid-quote. Table 3.5 also provides the outcome of testing whether the
Table 3.6: Spread for Absolute Price Change

This table shows spread estimates in cents based on absolute price changes for class A, B, C and D benchmark bonds as a percentage (×100) of the price. We test $Spread_{EMTS} = Spread_{domestic}$ using a standard t-test.

<table>
<thead>
<tr>
<th>Class</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euromts</td>
<td>BTP 15/07/05</td>
<td>BTP 01/03/07</td>
<td>BTP 01/08/11</td>
<td>BTP 01/05/31</td>
</tr>
<tr>
<td>Mts Italy</td>
<td>3.35</td>
<td>5.50</td>
<td>4.96</td>
<td>13.26</td>
</tr>
<tr>
<td>t-stat</td>
<td>2.02</td>
<td>3.38</td>
<td>3.20</td>
<td>8.39</td>
</tr>
<tr>
<td></td>
<td>2.06</td>
<td>1.68</td>
<td>2.29</td>
<td>1.18</td>
</tr>
<tr>
<td>Mts France</td>
<td>BTNS 12/07/05</td>
<td>BTNS 12/07/06</td>
<td>OAT 25/10/11</td>
<td>OAT 25/10/32</td>
</tr>
<tr>
<td>t-stat</td>
<td>4.34</td>
<td>10.38</td>
<td>6.82</td>
<td>17.54</td>
</tr>
<tr>
<td></td>
<td>4.92</td>
<td>5.48</td>
<td>7.58</td>
<td>35.64</td>
</tr>
<tr>
<td></td>
<td>2.33</td>
<td>1.20</td>
<td>0.45</td>
<td>1.61</td>
</tr>
<tr>
<td>Mts Germany</td>
<td>OBL 135 05/05</td>
<td>OBL 138 08/06</td>
<td>DBR 04/01/12</td>
<td>DBR 04/01/31</td>
</tr>
<tr>
<td>T-stat</td>
<td>3.78</td>
<td>4.01</td>
<td>16.99</td>
<td>17.89</td>
</tr>
<tr>
<td></td>
<td>3.09</td>
<td>3.76</td>
<td>9.16</td>
<td>16.18</td>
</tr>
<tr>
<td></td>
<td>0.79</td>
<td>3.04</td>
<td>0.53</td>
<td>1.44</td>
</tr>
<tr>
<td>Mts Belgium</td>
<td>OLO 34 09/05</td>
<td>OLO 37 09/06</td>
<td>OLO 36 09/11</td>
<td>OLO 31 03/28</td>
</tr>
<tr>
<td>t-stat</td>
<td>5.97</td>
<td>4.39</td>
<td>9.35</td>
<td>26.31</td>
</tr>
<tr>
<td></td>
<td>4.98</td>
<td>5.60</td>
<td>7.17</td>
<td>28.27</td>
</tr>
<tr>
<td></td>
<td>1.26</td>
<td>0.78</td>
<td>0.76</td>
<td>0.05</td>
</tr>
</tbody>
</table>

The effective (realized) spread on the EuroMTS is significantly 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

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

(3.5)

where $j = ask, bid$ and $z = bid, ask$. Table 3.6 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 3.1 shows the same information graphically. Table 3.6 also includes a test to see whether there exist significant differences between EuroMTS and the local trading platform. Some differences exist but the overall conclusion is that spreads across the different platforms are the same. Finally, we take a quick look at intraday spread patterns. Figure 3.2 shows the intraday pattern of quoted spreads for the most actively traded issue, the Italian 10-year bond. The quoted spreads show a typical U-shaped pattern. The trading day starts with a relative large spread around 3 cents in the early morning, falling to 2 cents in the late morning and gradually increasing to 4 cents in the late afternoon. Figure 3.3 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, this section provides some insights in the pricing behavior of market makers on both the local and EuroMTS trading platforms. 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 pattern across maturities. However, when testing differences in spreads between the domestic and EuroMTS platforms, we find that differences exist for a few bonds and in general, both markets are very integrated. Hence, there appears to be no difference between both markets with respect to the quoted bid-ask spreads. 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 a U-shaped pattern for the quoted spread.
3.4 The Price Impact of Trading

The analysis in the previous section provides us some useful insights in the trading costs on the MTS trading platforms. The provided measures of liquidity are however static and a dynamic structure will give us additional information for a number of reasons. First, dealers on the MTS are able to extract information from the live market pages of the system. Therefore, the actions taken by dealers not only depend on the concurrent price and trade but also on the previous changes in price and order flow. Manaster and Mann (1996) showed also the importance of lagged effects of order flows on futures prices on the CME. They argue that this is consistent with active position building. Second, previous observations of price and order flow are also important because the MTS trading system allows the splitting of orders. It is likely that the observed volume is the drip quantity instead of the total (block) quantity.

Trading intensity plays an important role in the study of price and order flow dynamics. 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 when noise traders are active (Kyle, 1985 and Easley and O'Hara, 1992) and this implies a positive relation between information and trading intensity.\(^\text{20}\) This means that any unexpected trade during strong trading activity has a higher impact on prices. On the other side, Diamond and Verrechia (1987) argue that informed traders always trade as they can take long or short positions. 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 increases the probability of facing an informed trader with bad news.

\(^{20}\)Kyle's (1985) model itself does explicitly make a statement about time as orders are aggregated. He does however argue that informed traders prefer to trade simultaneously with noise traders in order to minimize the chance of being detected. Easley and O'Hara (1992) argue that absence of trades reflects no-news creating a safer environment for a market maker to lower its spread.
who is constrained from selling short. Therefore, they expect a negative relation 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).

Empirical results so far suggest that a higher trading intensity is related to stronger price impacts. Dufour and Engle (2000) show that trading during busy periods is likely to be an informational event as the market maker increase its bid-ask spread in response to trades. Spierdijk (2002) also reports the same results. She shows using NYSE stock trading data that, during trading intensive sessions, a new trade has a larger impact on prices. Interestingly, the issue of price impact and varying trading intensity does not take the role of interdealer trading into consideration. We think that this is important for a number of reasons and we provide some arguments in the next subsection.

### 3.4.1 Trading Intensity and Interdealer Trading

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. There is however a small but important collection of theoretical papers on the behavior of market makers in a competitive setting. In these papers a crucial role is played by inventory. Ho and Stoll (1983) analyze the impact of inventory on trading behavior and argue that market makers having the largest long (short) position are first sellers (buyers). Biais (1993) analyzed the equilibrium number of traders in a competitive market setup and shows that the number of interdealer trades depends on the volatility of the security and the trading activity in the market. He also finds that the quoted spread around his reservation price is a decreasing function of the inventory. This supports the findings of Ho and Stoll. Empirical documentation suggests that interdealer trading is often used to control inventory. Manaster and Mann (1996) use CME Futures
transactions and find evidence that futures floor traders manage their inventory on a daily basis. They also find that dealers are liquidity providers who are willing to increase their position to speculate. Reiss and Werner (1998) provide a detailed study of inventory control among market makers on the London Stock Exchange. Using trading data, they test several hypotheses with respect to interdealer trading and find that 65% of all interdealer trades are used to reverse positions. This suggests that market makers use interdealer trades to reduce inventory risk. Hansch, Naik and Viswanathan (1998) use trading data from the London Stock Exchange and find that the mean reverting component in interdealer trading is time-varying but stronger compared to the traditional specialist markets as analyzed by e.g. Madhavan and Schmidt (1993). This suggests that it is easier to manage inventory using interdealer trading.

Although both the Reiss-Werner and Hansch et al. paper analyze the motives and characteristics of interdealer trades, they do not analyze the impact of these trades on price dynamics. We expect trades in an interdealer system during busy periods have a positive but smaller impact on prices than during quiet periods for a number of reasons.

The first reason is related to the searching costs for a counterpart. For example, Hansch. Naik and Viswanathan’s argument of a time-varying mean reversion in inventory depends on the searching cost for a counterpart. Reiss and Werner show the importance of trade anticipation in determining the dealer’s trade direction.

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21 The cost of this sure execution is the fact that you cannot sell (buy) at your own bid (ask) price but at other market makers ask (bid) price. These searching costs are already known from the limit book literature. See e.g. Foucault et al. (2001) and Parlour (1998) and references therein. Flood et al. (1999) also pointed this out in an experimental setting.

22 They note that if a order is anticipated, then "interdealer trades will precede customer trades in the same direction" e.g. if the dealer expects customer flows of buy trades, he will also start buying in the interdealer market. In contrast, if the order flow was unanticipated, “follow up trades will move in the opposite direction” e.g. unexpected customer buy trades will result in interdealer sell trades.
If a market maker anticipates incorrectly, he can correct his mistake more easily when trades arrive frequently. Ho and Stoll (1983) show that interdealer trading is more costly compared to outside customer trading. To control a position, a dealer can choose to wait until a trader enters the market (receiving a fee) or conduct an interdealer trade (paying a fee to the other dealer). Hence, the dealer's decision to conduct an interdealer trade depends on his ability to offset his inventory using customer order flow and this is easier when the trading activity is high. In other words, the searching costs for a counterpart are much lower during periods with customer order flow and this is more likely when trading intensity is high.

The second reason is the additional noise that arises when inventory is repeatedly passed among dealers using market orders. Lyons (1997) calls this repeated passing of inventory "hot-potato" trading and shows that this creates additional noise in the price process if dealers are risk-averse and speculative. Hence, the impact of an unexpected trade in a quiet trading environment may have a larger impact on the price (compared to a strong trading environment) because dealers are more likely to conduct an interdealer trade.

The third reason lies in the information asymmetry in government bond markets. Private information in government bond market however is fairly different from the information in stock markets, but comparable with the client based order flow information found by Lyons (1997). Evans and Lyons (2002) and Manaster and Mann (1996) show that client based order flows have a persistent impact on prices. Madhavan (1995) suggests that dealers may therefore narrow their spreads to attract customer flows in quiet trading periods. However, in order to provide a robust analysis of trading intensity in government bond markets, we have to incorporate the announcement of macroeconomic news. Fleming and Remolona (1999), Balduzzi, Elton and Green (2001) show that macroeconomic news produces an important impact on bond prices as the largest price movements arises in days with economic announcements. These papers find that before the announcement, trading intensity and price volatility is low while bid-ask spreads are high. Green (2004) documented
a higher adverse selection component after the announcement of news and argues that this is due to an increase in trading activity. Dealers absorbing large portions of order flow may have superior information about short-term price directions. This informational advantage will result in a dispersion of information among dealers and an increase in information asymmetry in the market. This rationale is fully consistent with the order flow information models by Lyons and Cao (1999), Fleming (2001) and Lyons (2001). Green (2004) also finds that prices are more sensitive to order flow in a period of increased liquidity after a scheduled announcement. Cohen and Shin (2003) also documents the same pattern. Because trading intensity is typically high during these periods, one can argue that prices are more sensitive to trading intensity (rather than less as suggested by the inventory rationale) as the urgency to trade becomes more important than the inventory control cost associated with interdealer trading. However, even during announcement days, we distinguish between periods with active and less active trading. Green (2004) for example states that after the announcement "market participants actively watch trading to help determine the effect of economic news." Hence, the more trading activity, the better signal the dealer receives with respect to the true impact of economic news.

Summarizing, order flow and trading intensity play an important role in interdealer trading. To avoid the costly interdealer trading, we expect prices to be negative correlated with trading intensity and this implies a higher price impact of trading under a low trading intensity. However, for government bond markets, the largest movements in prices occur when macroeconomic news is announced. In the specific case where news is announced, we would expect a stronger effect on prices during announcement days. Subsequently, the observations of trades to determine the effect of news in these situations is more valuable and a dealer would therefore prefer a strong trading intensity during these days. We are now ready to construct our econometric model.
3.4. THE PRICE IMPACT OF TRADING

3.4.2 Modeling Trading Intensity and Prices

In the previous section, we argued that the price impact of trading in an interdealer market is larger when trading intensity is low. To test this empirically, we have to model price impact by taking order flow dynamics and trading intensity into account. We apply the VAR model proposed by Dufour-Engle (2000). 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. 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 occurred on a domestic platform or on EuroMTS. The trading duration, $T_{t-i}$, is the difference in seconds between the time stamp for trade $t-i$ and trade $t-i-1$. Intraday data typically contain very strong diurnal patterns. Engle and Russel (1998) documented higher volatility at the 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 average trading duration in interval $\tau$ is given by $\bar{T}_\tau$ and trading duration is corrected for diurnal patterns by $T_{t-i}\bar{T}_\tau^{-1}$. 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 between trade $t-i$ and $t-i-1$ and hence the lower the trading intensity. With these ingredients, the full model becomes

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23 We add one second to the observed duration because some trades have exactly the same time stamp but a different transaction price.
\[ r_t = \alpha^r + \sum_{i=1}^{P} \left( 3^r_i + z^r_i \ln \frac{T_{t-i,T}}{T_\tau} \right) r_{t-i} + \left( \delta^r_0 D_t + \tau^r_0 \ln \frac{T_t}{T_\tau} \right) Q_t + \sum_{i=1}^{P} \left( \gamma^r_i + \delta^r_i D_{t-i} + \tau^r_i \ln \frac{T_{t-i,T}}{T_\tau} \right) Q_{t-i} + \varepsilon_{1,t} \]

\[ Q_t = \alpha^Q + \sum_{i=1}^{P} \left( \beta^Q_i + z^Q_i \ln \frac{T_{t-i,T}}{T_\tau} \right) r_{t-i} + \sum_{i=1}^{P} \left( \gamma^Q_i + \delta^Q_i D_{t-i} + \tau^Q_i \ln \frac{T_{t-i,T}}{T_\tau} \right) Q_{t-i} + \varepsilon_{2,t} \]

where the endogenous variables are \( r_t \) is the return in basis points and \( Q_t \) the signed quantity (in millions of Euro).\(^{21}\) Equations (3.6) is a typical vector autoregression with the coefficients being linear functions of trading duration \( T_{t-i,T} \) and a market dummy \( D_{t-i} \), which takes the value 1 if the trade at \( t \) occurred on the European MT and zero otherwise. Hence, the impact of a trade on the price movement depends on the quantity being traded \( (Q_t) \), the trading duration \( (T_{t-i,T}) \) and the trading platform \( D_t \). Notice that in this reduced form representation, the equation for return does not contain the contemporaneous effect of the order flow. We calculate \( \gamma_0^r \) from the estimated covariance of \( \varepsilon_{1,t} \) and \( \varepsilon_{2,t} \).

### 3.4.3 Empirical Results

In the estimation, we truncated the lagged variable at \( p = 3 \). In order to avoid the problem of heteroskedasticity, we calculate the White heteroskedastic consistent standard errors for statistical inference and report the resulting t-statistic. In order to preserve space, we focus our discussion on the Italian 2011 bonds because the results in this security are strongest. Table 3.7 gives an overview of the estimation results (\( \times 100 \)). Other bond series are discussed afterwards.

\(^{21}\)Hence, \( r_t = 10000 \ln (P_t / P_{t-1}) \) and \( Q_t \) is negative when a sell-order occurred while positive in case of a buy-order (from the perspective of the trade initiator).
3.4. THE PRICE IMPACT OF TRADING

Table 3.7: Estimation Results for the BTP 2011 Bond

Estimation of the Engle-Dufour model using Maximum likelihood. The t-statistics are based on White standard errors. The $\gamma_0$ coefficient is calculated using the correlation between the error terms. The left-hand side shows the estimation results for the return $r_t$ equation and the right-hand side shows the estimation result for the quantity $Q_t$ equation. For convenience, the coefficients are multiplied by 100.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Coefficient</th>
<th>t-statistic</th>
<th>Coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>-4.20</td>
<td>-2.47</td>
<td>0.17</td>
<td>0.11</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>1.04</td>
<td>0.97</td>
<td>-4.88</td>
<td>-3.19</td>
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<tr>
<td>$\beta_3$</td>
<td>-0.77</td>
<td>-0.93</td>
<td>-6.05</td>
<td>-3.99</td>
</tr>
<tr>
<td>$\gamma_0$</td>
<td>10.50</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>0.21</td>
<td>0.89</td>
<td>26.11</td>
<td>54.06</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>0.45</td>
<td>2.07</td>
<td>6.28</td>
<td>12.51</td>
</tr>
<tr>
<td>$\gamma_3$</td>
<td>0.35</td>
<td>1.83</td>
<td>4.64</td>
<td>9.46</td>
</tr>
<tr>
<td>$z_1$</td>
<td>0.57</td>
<td>0.50</td>
<td>2.33</td>
<td>2.18</td>
</tr>
<tr>
<td>$z_2$</td>
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<td>-1.84</td>
<td>3.13</td>
<td>2.90</td>
</tr>
<tr>
<td>$z_3$</td>
<td>1.23</td>
<td>1.69</td>
<td>4.38</td>
<td>4.07</td>
</tr>
<tr>
<td>$\tau_0$</td>
<td>4.62</td>
<td>15.40</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_1$</td>
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<td>-2.31</td>
<td>-4.16</td>
<td>-8.55</td>
</tr>
<tr>
<td>$\tau_2$</td>
<td>-0.29</td>
<td>-1.15</td>
<td>-4.26</td>
<td>-8.72</td>
</tr>
<tr>
<td>$\tau_3$</td>
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<td>-3.28</td>
<td>-6.89</td>
</tr>
<tr>
<td>$\delta_0$</td>
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<td>-9.37</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>-1.47</td>
<td>1.69</td>
<td>1.94</td>
</tr>
<tr>
<td>$\delta_2$</td>
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<td>2.83</td>
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</tr>
<tr>
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<td>1.76</td>
<td>3.63</td>
<td>4.18</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>-0.47</td>
<td>-0.56</td>
<td>8.48</td>
<td>3.63</td>
</tr>
</tbody>
</table>

We first turn our attention to estimation results of the return equation $r_t$. The parameters $\beta_1^Q$ and $z_1^Q$ gauge the impact of previous price movements on the concurrent price return. We find $\beta_1^r = -0.042$ and $z_1^r$ is insignificant. Hence, returns exhibit negative first order autocorrelation and independent from the trading duration. The $z_1^r$ parameter relates the change in $r_t$ on its own lagged values. Table 3.7 shows us that $z_2$ and $z_3$ are important and significant at a 10% confidence interval. The most important set of parameters for our investigation are $\gamma_1^r$, $\delta_1^r$ and
These parameters gauge the impact of order flows $Q_{t-i}$, the trading location $D_{t-i}$, and duration $T_{t-i}$ respectively. First, note that $\gamma_0 = 0.105$ and this implies that an instantaneous upward (downward) price movement is expected when a buy (sell) order occurs. Interesting are also the results for $\gamma_2 = 0.004$ and $\gamma_3 = 0.003$ which are both positive and significant at a 10% confidence level. These results show that (i) previous trades are also important and (ii) the impact of previous trades is also in the same direction, i.e. previous buy (sell) orders drive up (down) the current price. Subsequently, we also find that $\delta_0 = -0.025$ is significant while all other lagged market indicators are insignificant at 10% confidence level. This means that (all other things equal) the current trade has a lower impact on price on the EuroMTS compared to the domestic platform. Moreover, although previous trades are important, the location of these previous trades (domestic platform or EuroMTS) is unimportant. To see how the trading affects the price on this trading platform, consider a typical 5-million buy order entering the EuroMTS platform. The total impact is $5 \times (0.105 - 0.025) = 0.4$ basis point return. The same trade however has an impact of $5 \times 0.105 = 0.53$ basis points return on the local platform. Recall that $\tau_i^T$ reflects the interaction of trading duration on return $r_t$. Significant results are found for $\tau_0^T$, $\tau_1^T$ and $\tau_3^T$. First, $\tau_0^T = 0.046$ and this parameter gauges the instantaneous price reaction of an order. The fact that this parameter is positive implies that a buy-order after a longer period of inactivity, i.e. $T_{t-i}$, is large, will have a stronger instantaneous upward pressure on prices. Notice also that $\tau_i^T$, $i = 1, 3$ are negative, i.e. the price impact of previous buy-orders is gradually decreasing over time. As an example, consider a 5 million buy-order on the domestic platform at time $t^*$ since the previous trade. The expected instantaneous price reaction on a local market given this duration is given by $5 \times (0.105 + 0.046 \ln (t^*)) = 0.105 + 0.046 \ln (t^*)$. Clearly, the impact of a trade is an increasing function in $t^*$. Because we find a positive $\tau_0^T$, this implies that a transaction arriving after a long interval of inactivity has a stronger impact on trades than a transaction after a short interval of inactivity. This result contrasts the findings of

Let us now turn our attention to estimation results of the order flow equation $Q_t$. First, notice that the constant in our regression model is positive and significant differently from zero. Second, the parameters $\beta^Q_t$ and $\gamma^Q_t$ measure the impact of previous price movements $r_{t-1}$ on the order flow $Q_t$. As shown by table (3.7), we find negative and significant values for $\beta^Q_2$ and $\beta^Q_3$, which means that upward price movements in bonds are likely to be followed by sell orders. However, because $\gamma^Q_t$ is positive, this effect is gradually decreasing when previous orders where dated longer back in history. We also find that $\gamma^Q_t$ is positive and highly significant and this implies a strong autocorrelation in order flow, i.e. a buy (sell) order is likely to be followed by some additional buy (sell) orders. Hasbrouck (1991a) and Dufour and Engle (2000) also document the same finding. Negative values for $\gamma^Q_t$ however implies that this pattern decreases when duration is longer and activity is lower. However, because the duration coefficients $\gamma^Q_t$ are negative and significant, the autocorrelation effect is gradually decreasing over time. Notice also the positive and significant $\delta^Q_t$ parameters, which shows that the autocorrelation effect is stronger on the EuroMTS platform.

With respect to the results of the return equation for the other 2011 bond series, we do find differences between the domestic platform and EuroMTS in these markets: the $\delta_0$ parameter is significant for Belgium ($\delta_0 = 0.067$) and Germany ($\delta_0 = -0.226$). We do find a positive $\gamma_0$ for the other bond series, which runs from 0.007 for Belgium to 0.39 for Germany. The lagged variables $\gamma_0$ are not significant. We find a significant $\tau_0$ parameter for Belgium ($\tau_0 = -0.047$) and France

---

25Because the estimation results 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, which is $\chi^2_4$ distributed under the null-hypothesis. We reject the null-hypothesis.

26To preserve space, we do not present their estimation results. They are available upon request.
(\(\tau_0 = 0.035\)). The results for the BTP 2012 are given by \(\tau_0 = 0.054\) and again, a trade after a quiet period has a larger impact on price compared to the same trade in a busy period. Also, \(\delta_0 = -0.057\) and the total impact of a 5-million 'buy' trade on the EuroMTS platform is therefore \(5 \times (\tau_0 + \delta_0) = 0.44\) basis point return. The same trade however has an impact of some 0.72 basis point return on the local platform. For the other 2012 bond series, we cannot find any significant \(\tau_0\) and \(\delta_0\).

The empirical results so far do not take the announcement effect of macroeconomic news into consideration. Fleming and Remolona (1999), Balduzzi, Elton and Green (2001), Cohen and Shin (2003) and Green (2004) show that the largest price movements in government bond markets arises after the announcement of macroeconomic news. For example, Cohen and Shin (2003) analyzes the impact of trading on price dynamics on the US treasury market. Their VAR estimations are based on different sub-samples of high and low trading intensity. They find that the impact of trading on return during announcement days is larger compared to days without announcements. Interesting is their analysis of impulse response functions for 3 February 2000. This date was very volatile day with a lot of uncertainty concerning future supply of US treasuries. The nature of this shock, which occurred the day before\(^{27}\), 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. It is however interesting to see how trading responses to news. Green (2004) documented higher information asymmetry after the announcement of news because some dealers were able to absorb larger portions of order flows. These dealers may have superior information about short-term price directions. This informational advantage will result in a dispersion of information among dealers and an increase in information asymmetry in the market. This rationale is fully consistent with the order flow information models by Lyons and Cao

\(^{27}\)On February 2, the Treasury announced the reduction of future supply in the long end of the curve. This resulted in a significant flattening of the term structure.
3.4. THE PRICE IMPACT OF TRADING

(1999). Fleming (2001) and Lyons (2001). Green (2004) also finds that prices are more sensitive to order flow in a period of increased liquidity after a scheduled announcement. Cohen and Shin (2003) also documents the same pattern. Because of this information asymmetry, one can argue that the urgency to trade becomes more important than the costs associated with interdealer trading. To see how macroeconomic news affects the price dynamics, we divide our dataset into a sample with no news and a sample with macro-economic news announcements.

We re-estimate the Dufour-Engle model for the Italian 2011 bond by incorporating news with the highest trade impact by following the outcome of Fleming and Remolona (1999) and use the European equivalents of their outcome.\(^28\) We also include the US jobless claims, Producer Price Index, XAPM, consumer confidence and Fed fund target rates as these events are also awaited anxiously by European bond traders and therefore may have an impact on trading. Let us discuss the findings for \(\gamma_t^r\) (effect of signed quantity on return), \(\delta_t^r\) (effect of trading platform on return) and \(\tau_t^r\) (effect of duration on return).\(^29\) Because we focus on the return equation, we omit the superscript \(r\). Our data could be divided into days with no news announcements (40043 observations) and days with news announcements (105 days, 20781 observations). The effect of order flow on return is reflected by the \(\gamma_t\) parameters. First, the instantaneous impact of an incoming order is the largest for days with news announcements and the smallest for days without announcements (\(\gamma_0^{\text{news}} = 0.109\) versus \(\gamma_0^{\text{no-news}} = 0.104\)). The lagged variables \(\gamma_{t-1}\) are all positive but insignificant.\(^30\) The impact of a trade on return for the MTS and EMTS platform can be analyzed through the \(\delta_t\) parameters. We find that \(\delta_0\) is significant and smallest during days without news announcements (\(\delta_0^{\text{no-news}} = -0.0253\) versus

\(^{28}\text{We use the European employment numbers, ECB meetings, Producer Price index, Consumer Price Index, IFO survey, retail sales, gross domestic product, industrial production and consumer confidence.}\)

\(^{29}\text{The tables with estimation results are omitted here but available upon request.}\)

\(^{30}\text{The exception is } \gamma_3^{\text{news}} = 0.0065.\)
\( \delta_0^{(news)} = -0.0223 \). All other lagged market indicators appear not to be significant. Because this parameter is negative, it means that the impact is smaller on the EMTS trading platform but the difference becomes smaller during announcement days. Overall, the estimated magnitudes show that the instantaneous impact of a trade on the EMTS during an announcement day is larger compared to a non-announcement day and the difference for a 5 million Euro trade is 5 \( \times 0.008 = 0.04 \) basis point.\(^{31}\) Interesting are also the \( \tau \), parameters which reflect the impact of duration on return. Our estimates are positive, significant and larger for days without news announcements (\( \tau_0^{(no-news)} = 0.049 \) versus \( \tau_0^{(news)} = 0.043 \)). It shows that the instantaneous price impact of order flow is stronger in periods with macroeconomic news announcements but the impact is even stronger when trading intensity is low.

As a conclusive remark, the results for the Italian 2011 bond show that order flows are strongly correlated but this correlation pattern gradually decreases over time. In addition, not only does the current order have an impact on the price process but also previous orders. More importantly is the finding that orders on the Italian platform have a larger impact on prices compared to the EuroMTS although this finding is not supported by most bond series. In addition, the results also show that orders have a smaller impact on prices when trading intensity is large and this contrasts the findings of Dufour and Engle (2000) or Spierdijk (2002). The impact of incoming orders is also analyzed by dividing our dataset into days with and without macroeconomic announcements. We find the overall sensitivity during announcement days being larger and the sensitivity is magnified when trading intensity is fairly low. The latter implies that dealers are indeed watching order flow to determine the true effect of news.

\(^{31}\)Combining the results for \( \delta_0 \) and \( \tau_0 \), we find that the impact of a trade on the EMTS per 1 million Euro face value is the largest during announcement days \( \left( \delta_0^{(news)} - \delta_0^{(no-news)} \right) - \left( \tau_0^{(news)} - \tau_0^{(no-news)} \right) = 0.008. \)
### 3.4.4 Impulse Response Functions

In this section we focus on the impulse response functions using the estimated coefficients for the local trading platform.\(^3\) 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 5 million Euro's occurs in the market. Here, we use the average trading intensity for analyzing the systems dynamics and the model changes into

\[
\begin{align*}
    r_t &= \alpha^r + \sum_{i=1}^{p} \tilde{\beta}_i^r r_{t-i} + \sum_{i=0}^{p} \tilde{\gamma}_i^r Q_{t-i} + \varepsilon_{1,t} \\
    Q_t &= \alpha^Q + \sum_{i=1}^{p} \tilde{\beta}_i^Q r_{t-i} + \sum_{i=1}^{p} \tilde{\gamma}_i^Q Q_{t-i} + \varepsilon_{2,t}
\end{align*}
\]

which is the VAR model that Hasbrouck (1991) used. Again, we focus our discussion on the impulse response functions of the Italian securities which are given in figure 3.4. This figure also shows the impulse response function when a trade occurs 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. The lowest impact on the price process occurs when trading intensity is high. As we can see in the figures, an unexpected positive shock results in an instantaneous upward price movement between 0.4 basis points to 0.6 basis points for the BTP 2011 and 0.4 basis points.

\(^3\)The appendix provides details on the calculation of the impulse response functions.
to 0.9 basis points for the BTP 2012. The bid-ask bound arises in the second trade and this 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 by additional buy orders. The system therefore does not instantaneous move back to its equilibrium but it will take approximately 9 trades. 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 0.45 basis points to 0.9 basis points with the highest impact for periods in which trading intensity is low followed by average and high trading intensive periods.

We also computed the impulse response functions taking news announcements into account. As we can see in figure 3.5 and 3.6, the accumulated impact of a 5 million Euro buy trade has resulted in an 0.57 basis points increase in return in case when no news arrives and 0.64 basis points when news arrives. However, the impact is larger during periods with a higher trading intensity as the accumulated response stands at 0.65 basis points for no-announcement days and 0.7 basis points for announcement days.

3.5 Conclusions

This chapter focuses on the costs of trading European sovereign bonds. It offers some insights in the microstructure of the European government bond market using data from the MTS global market bond trading system. This platform is the largest pan European interdealer system in which market makers are obligated to quote two sides. Our analyses focus on the benchmark bonds from Belgium, France, Germany and Italy. An interesting feature of this market is that we have both a local and EuroMTS trading platform where the securities can be traded. At first sight, the EuroMTS platform appears to be redundant as the local markets provide a larger number of securities while attracting the largest part of the order flow. We analyzed
a number of reasons which might explained the existence of the EuroMTS platform. We first measured 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 spreads are smallest for the most actively traded issues such as the Italian 10-year bonds. For some securities there are small differences between the spreads on the MTS domestic trading platforms and EuroMTS. The domestic markets typically offer slightly better spreads (both quoted and effective) although differences are small, and if they exist, they turn into the local platforms' favor. Any reason favoring the existence of the EuroMTS system cannot be based to differences in spreads or price impacts of order flow. We think that this issue traces back to the request of treasury agents to have a domestic platform for monitoring rather than one dominant European platform. In addition, although the local systems provide a richer menu of bonds, some participants are willing to trade only the benchmark securities.

We then turned our attention to the price impact of trades and trading duration. The interdealer literature suggests that a key role is played by inventory control which depends on trading activity. Specifically, we argue that it is more difficult to control inventory when trading activity is low, increasing the search cost. Moreover, the information content of order flow and the repeated passing of inventory create additional noise in the price process. We analyze price discovery by adding parameters of trading intensity and lagged order flows, using 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. Finally, we divided our dataset into
days with and without important news announcements and re-estimate the model. We find that the impact of order flows is much larger under days with announcements. This effect is even magnified under low intraday trading intensity. Finally, when analyzing the price impacts of a trade, we find that the EuroMTS turns out to be a better channel for trading large trades although the reported differences are very small. We therefore conclude that both trading platforms are very much integrated.
3.A Appendix to Chapter 3

3.A.1 Appendix: Econometric Details

This appendix provides a discussion on the econometric method used in the Dufour-Engle model. Instead of estimating model (3.6) per equation, we estimate the model as a dynamic simultaneous equation model. Following Hasbrouck (1991a), we first rewrite the model into vector notation

\[
Y_t = \sum_{i=1}^{P} \tilde{A}_i Y_{t-i} + \tilde{a} + \sum_{i=1}^{P} \tilde{B}_i X_{t-i} + \sum_{i=0}^{P} \tilde{C}_i D_{t-i} Q_{t-i} + \tilde{G} Y_t + \tilde{F}_0 \ln T_t Q_t + \varepsilon_t
\]  

where

\[
Y_{t-i} = \begin{bmatrix} r_{t-i} \\ Q_{t-i} \end{bmatrix}, X_{t-i} = \begin{bmatrix} \ln(T_{t-i} T_t^{-1}) r_{t-i} \\ \ln(T_{t-i} T_t^{-1}) Q_{t-i} \end{bmatrix},
\]

and

\[
\tilde{a} = \begin{bmatrix} \tilde{a}_r \\ \tilde{a}_Q \end{bmatrix}, \tilde{A}_i = \begin{bmatrix} \tilde{A}_i^r \\ \tilde{A}_i^Q \end{bmatrix}, \tilde{B}_i = \begin{bmatrix} \tilde{B}_i^r \\ \tilde{B}_i^Q \end{bmatrix}, \tilde{C}_i = \begin{bmatrix} \tilde{C}_i^r \\ \tilde{C}_i^Q \end{bmatrix}, \tilde{C}_0 = \begin{bmatrix} \tilde{C}_0^r \\ 0 \end{bmatrix}, \tilde{F}_0 = \begin{bmatrix} \tilde{F}_0^r \\ 0 \end{bmatrix}, \tilde{G} = \begin{bmatrix} 0 & \tilde{G}_0 \end{bmatrix}
\]

Here the \( Y_t \) variables are endogenous as it contains the output of the system while \( X_t \) contains the observable input variables and therefore being exogenous. The reduced form of the \( t \)-th equation in model 3.8 is given by

\[
Y_t = (I_2 - \tilde{G})^{-1} \left[ \sum_{i=1}^{P} \tilde{A}_i Y_{t-i} + \tilde{a} + \sum_{i=1}^{P} \tilde{B}_i X_{t-i} + \sum_{i=0}^{P} \tilde{C}_i D_{t-i} Q_{t-i} + \tilde{F}_0 \ln T_t Q_t + \varepsilon_t \right]
\]

\[
= \sum_{i=1}^{P} \tilde{A}_i Y_{t-i} + \tilde{a} + \sum_{i=1}^{P} \tilde{B}_i X_{t-i} + \sum_{i=0}^{P} \tilde{C}_i D_{t-i} Q_{t-i} + \tilde{F}_0 \ln T_t Q_t + \varepsilon_t
\]  

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

For example

\[
\tilde{A}_i = \begin{bmatrix} \tilde{A}_i^r \\ \tilde{A}_i^Q \end{bmatrix} \equiv (I_2 - \tilde{G})^{-1} \tilde{A}_i = \begin{bmatrix} \tilde{A}_i^r + \tilde{G}_0 \tilde{A}_i^Q \\ \tilde{A}_i^Q \end{bmatrix}
\]

\[
(3.13)
\]
The error term is $v_t \sim N(0, \Xi_t)$ where $\Xi_v = (I_2 - G)^{-1} \Xi_0 (I_2 - G)^{-1}$. The model as such is not identified as we cannot track the structural parameters using its reduced form (3.12). This identification problem arises as the reduced model is not able to identify the $\gamma^*_0$ parameter of the original model without some additional restrictions on the model. However, we can calculate its value from the relation $v_{1,t} = \varepsilon_{1,t} + \gamma^*_0 \varepsilon_{2,t}$ which implies

$$\gamma^*_0 = \frac{\text{cov}(v_{1,t}, v_{2,t})}{\text{var}(v_{2,t})}$$

(3.14)

The $\gamma^*_0$ parameter can be interpreted as the instantaneous impact of an incoming trade on the return residual and therefore on return itself. It must be non-negative due to a bid-ask price. 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 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 (3.8) with the upper Choleski decomposition of the residuals variance-covariance matrix $\Xi_v$. Because our model contains AR-terms, it is useful to rewrite model (3.12) compactly in its final form for estimation purposes

$$Y_t = A(L)^{-1} [a + B(L) X_t + C(L) D_t Q_t + F_0 \ln T_t Q_t + v_t]$$

(3.15)

and we calculate the joint density of the endogenous variables using Maximum Likelihood.

An illustration of this method is given in Hamilton (1994).\footnote{Here, $Z_t = (x_t, X_t, D_t Q_t, \ln T_t Q_t), A = \text{var}[\alpha, \Phi_1, \Phi_2, \Phi_3]$ and $u_t = A(L)^{-1} v_t$. The lag operators are defined as $A(L) = I_2 - \sum_{i=1}^{p} A_i L^i, B(L) = \sum_{i=1}^{p} B_i L^i, C(L) = \sum_{i=0}^{p} C_i L^i$ and $\Phi_1 = A(L)^{-1} B(L), \Phi_2 = A(L)^{-1} C(L)$ and $\Phi_3 = A(L)^{-1} F_0$. The final form representation implies that $Y_t|Y_{t-1} \sim N \left( Z_t A_t, A(L)^{-1} \Xi_t A(L)^{-1} \right)$}

3.A.2 Appendix: Impulse Response Functions

We now turn to the calculation of the impulse responses for the local trading plat-
form. 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(\infty) 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 (3.12).

\[
\begin{align*}
\text{r}_t &= \alpha^r + \sum_{i=1}^{P} \left( \beta_i^r + z_i^r \ln \frac{T_t - i, \tau}{T_\tau} \right) r_{t-i} + \tau_0^r \ln \frac{T_t, \tau}{T_\tau} Q_t \\
&\quad + \sum_{i=1}^{P} \left( \gamma_i^r + \tau_i^r \ln \frac{T_t - i, \tau}{T_\tau} \right) Q_{t-i} + \nu_{1,t} \\
Q_t &= \alpha^Q + \sum_{i=1}^{P} \left( \beta_i^Q + z_i^Q \ln \frac{T_t - i, \tau}{T_\tau} \right) r_{t-i} \\
&\quad + \sum_{i=1}^{P} \left( \gamma_i^Q + \tau_i^Q \ln \frac{T_t - i, \tau}{T_\tau} \right) Q_{t-i} + \nu_{2,t}
\end{align*}
\tag{3.16}
\]

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

\[
I_r(n, \varepsilon_{2,t} = \delta, \Omega_{t-1}) = E[r_{t-n} | \varepsilon_{2,t} = \delta, \varepsilon_{t-1} = \ldots = \varepsilon_{t-n} = 0, \Omega_{t-1}] \\
- E[r_{t-n} | \varepsilon_{2,t} = 0, \varepsilon_{t-1} = \ldots = \varepsilon_{t-n} = 0, \Omega_{t-1}]
\tag{3.17}
\]

Here the first term of (3.17) reflects the system when it has been hit only once by a shock \( \delta \) 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 \( \Omega_{t-1} \), 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 that the impulse response function of linear models does 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 (3.16).

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 (3.16) changes into a linear VAR(\( p \)) model.

\[
\begin{align*}
\tau_t &= \sum_{i=1}^{P} \beta_i^\tau \tau_{t-i} + \sum_{i=1}^{P} \gamma_i^\tau Q_{t-i} + v_{1,t} \\
Q_t &= \sum_{i=1}^{P} \beta_i^Q \tau_{t-i} + \sum_{i=1}^{P} \gamma_i^Q Q_{t-i} + v_{2,t}
\end{align*}
\]  

(3.18)

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 one unexpected trade is conducted in a period of high and low trading intensity. To do so, we use the 10-th percentile trade based on the distribution of \( \tau_{\text{high}} = [10.00 - 10.30] \) am interval and the 90-th trade based on the distribution of \( \tau_{\text{low}} = [17.00 - 17.30] \) 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 \( T_{t-i, \tau}^{\text{high}} \) and \( T_{t-i, \tau}^{\text{low}} \) such that

\[
\begin{align*}
\tau_{t-i, \tau}^{\text{high}} &= 10th-\text{percentile trade in interval } \tau = \tau_{\text{high}} \\
\tau_{t-i, \tau}^{\text{low}} &= 90th-\text{percentile trade in interval } \tau = \tau_{\text{low}}
\end{align*}
\]  

(3.19)

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

\[
\begin{align*}
\tau_t &= \alpha^\tau + \sum_{i=1}^{P} \beta_i^\tau \tau_{t-i} + \tau_0^\pi \pi_0 Q_t + \sum_{i=1}^{P} \gamma_i^\tau Q_{t-i} + v_{1,t} \\
Q_t &= \alpha^Q + \sum_{i=1}^{P} \beta_i^Q \tau_{t-i} + \sum_{i=1}^{P} \gamma_i^Q Q_{t-i} + v_{2,t}
\end{align*}
\]  

(3.20)

where \( \pi_0 \) is either \( \frac{\tau_{\text{high}}}{\bar{T}_\tau} \) or \( \frac{\tau_{\text{low}}}{\bar{T}_\tau} \).
Note that the dynamics of system (3.18) and (3.20) 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($\infty$) model as the orthogonal innovations do not obscure the actual reaction towards the system. For example, both (3.18) and (3.20) can be written as $Y_t = \varepsilon_t + \sum_{i=1}^{\infty} \theta_i \varepsilon_{t-i}$, where the matrix $\theta_n$ has the interpretation $\partial Y_{t-n} = \theta_n \partial \varepsilon_t$. Instead of this MA($\infty$) approach, we continue to use the reduced form of system (3.16) and follow the approach of Lütkepohl (1994), page 51, which requires the use of a Choleski decomposition of the variance matrix.
3.B Graphs Chapter 3

Figure 3.1: The estimated spread based on absolute price differences on the MTS versus the EMTS. Data runs from 4 February 2002 until 15 February 2002.
3.B. GRAPHS

Figure 3.2: Intraday pattern of quoted spread for the BTP 2011.

Figure 3.3: The average effective and realized spread.
Figure 3.4: Impulse response function for the Italian 2011 bond
Figure 3.5: Impulse response function for the Italian 2011 bond (No news announcements)

Figure 3.6: Impulse response function for the Italian 2011 bond (News announcements)