Informed trading in hybrid bond markets

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Abstract

This paper investigates whether establishing an electronic limit order book (LOB) in a current over-the-counter (OTC) bond market will move the price discovery process onto the new venue and if so, whether informed traders supply or demand liquidity. A detailed data set from the hybrid Norwegian government bond market shows that informed dealers prefer market orders in the LOB. The results further show that uninformed dealers tend to provide liquidity to informed dealers. Informed dealers' preference for speed can reflect that limit orders and OTC trading are exposed to waiting costs which can be substantial in many bond markets. These findings suggest that recently proposed pre-trade transparency requirements will contribute to a more efficient price discovery process in current OTC bond markets and that an incentive scheme for liquidity suppliers could enhance it further.

JEL Classification: G12, G14, G17.

Keywords: Bonds, informed dealers, order flow, predictability, transparency, waiting costs.

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1 Introduction

Yield curves provide essential information to borrowers and investors as well as input to measures of credit risk, liquidity risk, and inflation expectations. The accuracy of this information depends on the efficiency of the bond prices employed. A number of bonds, including corporate bonds, municipal bonds, and some segments of government bonds, are currently trading in opaque over-the-counter (OTC) markets.[1] The lack of transparency makes it difficult to obtain prices, especially in periods of frequent news arrivals and in times of market stress. After the financial crisis regulators have proposed new pre-trade transparency requirements in an effort to move trading from opaque OTC-markets onto lit electronic limit order books (LOBs) where prices are transparent. Green et al. (2010) further find that the lack of transparency in the municipal bond market results in a slow price discovery process. While it would be interesting to know whether such reforms would facilitate a faster price discovery process, the purpose of this paper is to study whether the introduction of a transparent LOB will shift the price discovery process onto the lit venue and thus improve the efficiency of observable bond prices as information aggregators.

To address potential effects of new transparency requirements on the price discovery process in current OTC bond markets this paper investigates the choice of trading venue and order type by informed dealers in a hybrid market.[2] Informed dealers, defined as dealers whose order flows can predict bond excess returns, can choose between three major trading strategies including market and limit orders in the LOB and trading in the OTC-market. While market orders in the LOB are fast to execute and have high trading costs, market orders in the OTC-market have lower trading costs, but require more time to execute. Limit orders in the LOB have the lowest trading costs, but contain execution risk and thus waiting costs. The chosen trading strategies reveal each dealer's trade-offs between speed, trading costs, and execution risk when they possess private information.

[1] In OTC bond markets a trader negotiate a trade over the phone or via platforms like Tradeweb where traders can request quotes from many dealers simultaneously. The trader will then contact the dealer providing the best quote.

[2] A hybrid market is defined by Foucault et al. (2013) as a market design that mixes features of two or more market types.

The paper makes three contributions to the empirical market microstructure literature. First, it provides a unique insight into the actual trading strategies by five heterogeneously informed bond dealers. The complete trading records of these dealers are analyzed over a 13 year period following the introduction of a LOB in 1999. Using a clean data set with identifiers for trading venue, order type, and the names of the buying and selling dealers the paper studies the five dealers' choice between the two venues for the period 1999-2005 and the choice between market orders and limit orders in the LOB for the whole 1999-2012 period. The period covering venue choice is shorter due to the end of an informal agreement to continue quoting to each other in the OTC market in mid-2005. Other studies exploring the trading strategies of informed traders use more restricted data sets related to stock markets. Reiss and Werner (2005) use trade settlement data with dealer identities from the London Stock Exchange to study the dealers' choice between two OTC trading venues with different degrees of transparency. Kaniel and Liu (2006) examine whether limit orders or market orders are more informative at the NYSE, but cannot distinguish between traders. This paper adds to the literature by addressing both the choice of trading venue and the choice of order type by individual dealers.

Second, the paper employs the predictive power of individual order flow as a measure of informed trading. Using the framework of Goyal and Welch (2008) the paper discloses periods when a dealer has an information advantage and her chosen trading strategy at that time. This is accomplished by dividing order flows into different types according to venue and order type and then testing the out-of-sample predictive power of each order flow type.[3] The paper displays the predictive power of each dealer's order flow types over time which also reveals their chosen trading strategies over time. Previous studies use different methods to identify informed traders. Reiss and Werner (2005) and Kaniel and Liu (2006) use intraday changes in quotes following trades for shorter periods during 1990 and 1991.[4] Boulatov et al. (2013) use

[3] Order flow is defined as the number of buyer-initiated trades minus the number of seller-initiated trades during a day. A positive order flow indicates a net buying pressure and a negative order flow indicates a net selling pressure.

[4] Reiss and Werner (2005) identify informed trades by the subsequent price impact on the dealers' quotes. Kaniel and Liu (2006) measure the informativeness of market-buys at a one day horizon is defined as the ratio of the number of times the quote midpoint a day after a submission of a market-buy is higher than the one

aggressive institutional order flow as a proxy for informed trading while Collin-Dufresne and Fos (2015) use trades by investors who have filed according to Rule 13d-1(a) indicating that they have an interest in influencing the management of the company. This paper contributes to the literature by identifying informed traders by using the predictive ability of their order flows.

Third, the paper contributes to the debate on market reforms in previosly opaque markets. By revealing the trade-offs between speed, trading costs, and execution risk in a bond market with infrequent trading, policy makers can evaluate the need for establishing a market-maker system to secure liquidity provision on a transparent venue. There are a few empirical studies documenting the effects of increased post-trade transparency in OTC-markets. Goldstein et al. (2007), Bessembinder and Maxwell (2008), and Asquith et al. (2013), and Li and Schurhoff (2014) document the effects of post-trade transparency on trading costs in corporate and municipal bond markets. However, little is known about the effects of pre-trade transparency. This paper contributes to the literature by analyzing the effects of pre-trade transparency on price discovery in previosly opaque markets.

The results show that informed dealers prefer the transparent LOB to the opaque OTC-market. During the period from 1999 to 2005 order flows based on market orders in the OTC-market have little predictive power while order flows based on market orders in the LOB have significant predictive power for four of the five dealers. Trading costs measured by the average half spread are 3 to 7 basis points higher in the LOB than in the OTC-market in the same period. The preference for market orders in the LOB among all the informed dealers suggests that waiting costs are higher in the OTC-market.

Waiting costs represent additional costs in the OTC-market related to information decay over time. If private information is short-lived or difficult to hide in the OTC-market and the trading process takes time and involve several liquidity providers, for example via web requests, other dealers can aquire the information and trade in front. This will move the price and erode the original information advantage, referred to as "slippage" by Rosu (2015). Unintended disclosure of private information is plausible in OTC markets with a few central

prior to submission to the number of market buy order submissions.

dealers. Li and Schurhoff (2014) find that the large municipal bond market is chatacterized by a few central dealers who are involved in the majority of trades. Dealers with valuable private information are thus likely to pay the extra costs in the LOB to avoid a loss to other dealers who can trade in front. These results are in line with Menkveld et al. (2014) who find a pecking order of trading venues where the transparency of the venue selection increases with investor urgency.

The results further show that informed dealers prefer market orders to limit orders in the LOB. During the period from 1999 to 2012 order flows based on market orders in the LOB have significant predictive power with the "right" coefficient sign for all dealers, while order flows based on limit orders, passive order flows, have significant predictive power with the "wrong" sign. The signs are expected to be positive when a dealer trades on information because a dealer expecting a higher future value will buy the bond. However, the coefficients for the passive order flows are negative suggesting that the predictive information stems from the dealer's counterparties. The strong significance for some dealers suggests that their counterparties are informed dealers who are adversly selecting other dealers' limit orders. Interestingly, the dealer whose passive order flow has the strongest out-of-sample predictive power has the weakest predictive power based on LOB order flow.

The preference for market orders over limit orders is likely to reflect that limit orders have waiting costs. According to Foucault, Kandan, and Kandel (2005) waiting costs increase with the expected time to execution. This time is negatively related to the trading frequency in the market and thus higher in OTC bond markets than in stock markets and on-the-run government bond markets. Limit orders posted by informed dealers are likely to have high waiting costs mainly consisting of slippage costs according to Rosu (2015) who defines these costs as the decay of the original information advantage. In bond markets with infrequent trading these waiting costs are expected to be high. ch higher than the comparable cost in the OTC-market. This decay cost is higher than the spread in the LOB, which on average was 8 to 16 basis points over the whole period, and reflect that transparent limit orders in markets with infrequent trading activity are exposed to competition from future informed traders.

Informed dealers with profiable private information will thus choose the most transparent, and fastest, trading venue. In all, the results in this paper suggest that introducing pre-trade transparency in OTC bond markets will improve the price discovery process as informed trades will migrate from the opaque to the transparent venue. However, securing liquidity provision in such a marked may require a system of compensated market-makers.

The rest of the paper is organized as follows. Section 2 gives a brief overview of the related literature. Section 3 describes possible trading strategies for informed dealers. Section 4 presents the Norwegian government bond market and the data set. Section 5 presents the econometric framework, reports the results, and discusses the trade-offs between speed, trading costs, and execution risk. Section 6 concludes.

2 Related literature

This paper is related to several fields of the empirical finance literature. First, it is related to the literature on transparency and informed trading. Kaniel and Liu (2006) analyze informed traders equilibrium choice of limit or market orders. They find that informed traders prefer market orders if the information is short-lived and limit orders otherwise. Zhu (2014) presents a model of strategic venue selection where traders can choose between trading via an exchange or a dark pool. He finds that informed traders face high execution risk in dark pools and therefore lit exchanges are more attractive to informed traders. Bessembinder and Venkataraman (2004) investigate large (block) trades in the OTC-market (upstairs market) and LOB (downstairs market) on the Paris Bourse for the period 1987/88 and find that both execution costs and information content are lower in OTC trades than in LOB trades. Reiss and Werner (2005) study the direct (non-anonymous) interdealer market and the indirect (anonymous) market via brokers comprising the OTC-market at London Stock Exchange in 1991. They investigate which venue UK stock dealers prefer and find that informed dealers tend to prefer the non-anonymous market. This paper extends this literature by studying pre-trade transparency in bond markets, which have a different structure and trading frequency than stock markets.

Second, it is related to the market microstructure literature on the information content in order flow. Several empirical studies show the importance of aggregate order flow in the price discovery process and document that order flow reflects private information about asset prices.[5] Hasbrouck (1991), Evans and Lyons (2002), and Brandt and Kavajecz (2004) among others, show that order flow contains private information about contemporaneous changes in stock prices, exchange rates, and bond yields, respectively. Evans and Lyons (2005) further show that order flow predicts future asset prices both in- and out-of-sample.[6] This paper adds to the previous literature by documenting that bond market order flows contain information about future bond excess returns, and that the predictive power varies across different trading venues and order types.

Third, the paper is related to the extensive literature on asset price predictability. Goyal and Welch (2008) reexamine the performance of variables that have been suggested to be good predictors of the equity premium. They monitor the predictive power of the these predictors relative to a naive benchmark using the historical average as the predictor over the whole sample period by illustrating graphically the cumulative squared prediction errors of the benchmark model minus the squared prediction errors of the alternative model. They find that most of the models are unstable or even spurious and recommend that a predictor variable is tested both in-sample and out-of-sample. This paper applies their framework to identify informed traders by employing individual dealer order flows to predict bond excess returns on a daily basis. This enables the paper to compare the information advantage possessed by each of the five dealers over the whole 13 year period.

3 Informed trading strategies

Informed dealers can choose between four basic trading strategies in the hybrid interdealer market. The first is submitting a market order in the LOB, the second is submitting a

[5] Positive order flow indicates positive information about the asset value and negative order flow indicates negative information.

[6] Evans and Lyons (2005) document that order flow has predictive power for future exchange rates both in-sample and out-of-sample. Valseth (2012) documents that bond market order flow has predictive power for bond excess returns above that of forward rates in the Norwegian government bond market.

limit order in the LOB, the third is contacting a dealer to submit a market order in the OTC-market, and the fourth is providing liquidity in the OTC-market. The last strategy, which implies waiting until another trader in the OTC-market is requesting a quote, is not considered in this paper because of the high execution risk, especially in markets with low trading frequency.[7] While the first strategy secures immediate trade execution, the two other strategies involve waiting time from the trade decision is made until the trade is executed. Trading costs, measured by the spread, are highest for the first strategy and lowest for the second strategy. However, waiting time incurs waiting costs because of the risk that prices move in the adverse direction.

To illustrate the trade-offs between the two first trading strategies I use the framework of Foucault, Kandan, and Kandel (2005). They develop a model of price formation in a limit order market with strategic traders and waiting costs. Waiting costs are proportional to the expected waiting time and consist of two components, the expected time to execution and the cost of delaying execution per unit of time. The model includes two types of traders, patient or impatient, and illustrates the effects of low trading frequency, which implies longer waiting time, and impatience, which implies higher waiting costs per unit of time, on their order choice. Both types of traders face a trade-off between the cost of speed and the waiting cost. The waiting cost per unit of time is higher for informed (I) than for uninformed traders (U) because their expected profit by trading on private information will decrease if prices move in a unfavorable direction. In this paper I assume that informed dealers are impatient while uninformed dealers are patient. Prices and spreads in the Foucault, Kandan, and Kandel (2005) model are measured in number of ticks while dealers' valuations, trading costs and profits are measured in monetary terms. The inside spread is defined as

$$s = a - b, \tag{1}$$

where s is the spread, a is the best ask, and b is the best bid in multiples of the tick size.

[7] Another strategy which is not considered is to place a limit order in the OTC-market. This strategy is more likely in the dealer-customer market than in the interdealer market, which is the focus in this paper.

From Equation (1) it follows that a submission of a buy limit order inside the spread will increase b and thus reduce the spread. The execution prices for buyers and sellers can be expressed as $p_{buyer} = a - j$ and $p_{seller} = b - j$ for $j \epsilon \{0, 1.., s-1\}$ where $j = 0$ is a market order and $j > 0$ is a limit order creating a spread of j ticks. The expected time to execution of a j-limit order is $T(j)$ where $T(0) = 0$ for a market order with immediate execution and $T(j) > 0$ otherwise. The expected profit for dealer i, who wants to buy the security, by submitting a j-limit order can then be expressed as

$$\pi_i(j) = V_{buyer} - p_{buyer}\Delta - \delta_i T(j) = V_{buyer} - a\Delta + j\Delta - \delta_i T(j), \tag{2}$$

where $\pi_i(j)$ is the expected profit of dealer i, Δ is the tick size in monetary terms, V_{buyer} is the value for the buyer, $p_{buyer}\Delta$ is the purchase price, and $\delta_i T(j)$ is the expected waiting cost. From Equation (2) it follows that the purchase price can be decomposed into the best ask price, $a\Delta$, which is the price if the dealer submits a buy market order, and the price improvement, $j\Delta$, when the dealer submits a buy j-limit order which creates a new, smaller spread, $j\Delta$. The expected waiting cost for each type of dealer is the product of expected time to execution, $T(j)$, and the waiting cost per unit of time, δ_i, for dealer type i where $\delta_I > \delta_U$. The waiting costs for informed and uninformed dealers can thus be expressed as $\delta_I T(j) > \delta_U T(j)$ respectively. The choice of trading strategy thus depends on which j-limit order will maximize their expected profit

$$\max_{j \epsilon \{0, \ldots s-1\}} \pi_i(j) = j\Delta - \delta_i T(j), \tag{3}$$

where $\pi_i(j)$ is the expected profit by a dealer of type i. An informed dealer submits a j-limit order ($j \neq 0$) only if the price improvement exceeds the waiting cost, $j\Delta > \delta_I T(j)$. Otherwise the dealer chooses a market order and the profit, $V_{buyer} - a\Delta$, will be certain. Equation (3) shows that the choice of trading strategy for both types depends on the size of the spread, which determines the maximum price improvement achievable, and the on the expected waiting time.

Foucault, Kandan, and Kandel (2005) assume that traders arrive to the market according to a Poisson process with parameter $\lambda > 0$. The number of traders during a time interval of length τ will then be distributed according to a Poisson distribution with paramenter $\lambda\tau$ and the average time between arrivals will be $\frac{1}{\lambda}$. The authors further assume that $T(j)$ is non-decreasing in j and show that the expected waiting time of a $j = 1$-limit order is $\frac{1}{\lambda}$. Since a trader submitting a limit order has to wait to execute the trade at least until the next trader arrives, the expected waiting cost will be minimum $\frac{\delta_i}{\lambda}$ for dealer i. Given the spread size and trading frequency, a higher value of δ_I makes it more likely that waiting costs exceed the possible price improvement by submitting limit orders in which case the informed dealer will choose a market order instead of a limit order in the LOB.

However, informed dealers in the hybrid Norwegian government market have a third possible trading strategy, market orders in the OTC-market. What are the trade-offs facing dealers considering all three strategies? I employ the framework of Foucault, Kandan, and Kandel (2005) for OTC-trades and let the price improvement relative to a market order in the LOB, $j^{OTC}\Delta$, will be the difference between the half-spread in the LOB and the OTC-market.[8] The waiting cost will depend on the time it takes from an informed dealer contacts another dealer until the initiating dealer accepts a quote as well as the waiting cost per unit of time. While the waiting time for a market order in the OTC-market is likely to be shorter than for a limit order in the LOB, the waiting cost per unit of time can be higher. This will be the case if informed dealers have difficulty hiding their private information when trading in the OTC market. If the quoting dealer understands that her counterparty trades on private information she can try to front-run the trade in an illiquid market and thus reducing the former's expected profit. As many OTC bond markets are characterized by a few central dealers who handles a majority of the trades this is not an unlikely outcome for an informed trader. This is the case both in the Norwegian government bond market and in the US corporate and municipal bond markets dokumented by Bessembinder and Maxwell (2008) and Li and Schurhoff (2014), respectively. If a dealer instead submits a market order in the LOB this risk of being front run will be eliminated. Also, if an informed dealer submits a limit order in

[8] I assume that the mid-point is equal in the LOB and the OTC-market.

the LOB, the risk that other dealers learn about the private information is likely to be much less. In the LOB a dealer can break up a large informed trade into several limit orders. Other dealers cannot easily distinguish informed limit orders from uninformed limit orders in the LOB.

The expected profit for an informed dealer of a market order in the OTC-market relative to a market order in the LOB can be expressed as

$$\pi_I(j^{OTC}) = j^{OTC}\Delta - \delta_I^{OTC}T(j^{OTC}), \tag{4}$$

where $T(j^{OTC})$ is the expected waiting time for the OTC market order to be executed so that $T(j^{OTC}) < T(j)$, $j^{OTC}\Delta$ is the price improvement, and δ_I^{OTC} is the waiting cost per unit of time in a OTC bond market. If $T(j^{OTC})$ is smaller and δ_I^{OTC} higher in the OTC-market compared to a limit order in the LOB and $j^{OTC}\Delta$ is smaller it is possible that the expected profit of a market order in the OTC-market is zero or negative.

Many bond markets currently organized as OTC-markets have relatively low trading frequency which implies a high expected waiting time for limit orders.

If we assume that τ is one day, the daily trading frequency in the market can be employed to approximate the minimum expected waiting time and the minimum waiting cost for an informed dealer.

The risk of worse prices related to delayed or no execution incurs waiting costs.

[9] Rosu (2015) defines slippage as the tendency of an informed trader's estimated mispricing to decay over time due to the future arrival of other informed traders who correct the mispricing by submitting their orders.

An important characteristic of many bond markets is that the trading frequency is low. This as the time from a limit order is posted until a potential trader arrives in the market can be long incurs waiting costs. Barclay, Hendershott, and Kotz (2006) finds that recent

[9] It is important to note that the risk related to placing a limit order differs according to whether the dealer is informed or not. An uninformed dealer placing a limit order faces adverse selection risk only.

off-the-run Treasuries trade about 20 times per day and far off-the-run securities even less. Goldstein (2013) reports that in the corporate bond market the number of trades per bond are on average 50 per day. The median number of trades per day is only 14 and the number of non-trading days is large for many corporate bonds. Hollifield (2013) reports that municipal bonds on average trades 3 times per year and that 70 percent never trade after issue. The number of trades in the Norwegian government bond market, which includes 4-6 issues with maturities between 1 and 11 years, were 45 per day in the 1999-2005 period and about 20 per day in the 2005-2012 period.[10]

Example: Macroeconomic news (MPC meeting January 28, 2004 (expcted decrease in rate of 0,25 which was realized) around this time the quoted spread was 0,23 bps (ticks) and the standard deviation of the best bid quote 0,23 bps)

I

To identify periods when dealers are informed the paper explores the predictive power of the dealers' order flows over time by employing the framework of Goyal and Welch (2008). The analysis thus captures the periods, if any, when any of the dealer's order flows in the LOB or the OTC-market contain information about the future bond excess returns. Dealers are defined as trading on information if their interdealer order flow predicts next day bond excess returns and the sign of the coefficients is positive. Dealers are defined as uninformed if their order flow have no predictive power at all. If the order flow has predictive power and the sign is negative it is the counterparties to the trades included in the order flow measure that are informed. [11]

Depending on which of the three types of order flows have predictive power the paper infers the preferred trading strategies of informed dealers. On the basis of these choices the results in this paper also sheds light on the slippage costs related to limit orders in bond markets. Many bond markets have a much lower trading frequency than stock markets and this may influence the size of the decay costs. The results can be used as a guide to the

[10]Excluding repos.

[11]A negative coefficient implies that a net purchase predicts a fall in next day excess returns.

market set-up when implementing the proposed pre-trade transparency requirements.

To disentangle the types of information possessed by dealers and reflected in their order flows I employ dummy variables for macroeconomic news days and days with large trades. If the absolute size of a dealer's order flow is significantly higher on news days, and this order flow has predictive power, it points to fundamental macroeconomic information as the source of private information.[12] If the absolute size of a dealer's order flow is significantly higher on days with large trades, and this order flow has predictive power, it points to non-fundamental information in large orders as the source. If none of the dummies are significant, and order flow has predictive power, there could be some other source of private information, for example international macro news or liquidity conditions. The type of information combined with the preferred trading strategies by informed dealers can thus shed light on which type of private information that potentially creates large mispricings in the market.

4 The Norwegian government bond market

4.1 Market overview

The secondary market for Norwegian government bonds is, like many other sovereign bond markets, organized as a hybrid market consisting of an electronic limit order book (LOB) and an over-the-counter (OTC) market.[13] Only dealers who are members of the Oslo Stock Exchange (OSE) and authorized to trade in bonds have access to the LBO. Authorized dealers include banks and brokerage firms, and are referred to as dealers. Non-exchange members, have no direct access to the LOB and are referred to as customers. Customers include institutional investors, leveraged investors, commercial firms, and individual investors and can only trade via dealers. Dealers thus have a choice of trading venue while customers can only trade in the OTC-market.

A system of primary dealers is administered by the central bank to promote orderly

[12] I use the absolute value of order flow to capture positive and negative news and buyer-initiated and seller-initiated large trades as these will have opposite effects on order flows and bond prices.

[13] "Over-the-counter" trades are agreed on over the phone or any communication systems other than the electronic order book.

markets. Primary dealers are appointed to perform market-making services and account for a large share of total trading volume. The number of primary dealers in Norway has varied between 8 and 4 during the sample period. Primary dealer obligations include posting of firm bid and ask quotes in the LOB during the trading day (9 am-4 pm). For the first few years after the inception of the LOB in 1999 dealers agreed to continue quoting prices to each other in the OTC-market. Around mid-2005 this informal agreement was terminated. About 12 dealers, of which half primary dealers, were active market participants up to this time. After this period the number of primary dealers gradually declined to 4 in 2011, and the share of interdealer trading volume in the OTC-market dropped substantially.

The LOB is administered by the Oslo Stock Exchange (OSE) and has features similar to other electronic trading systems such as the MTS system. An important difference between the LOB and the OTC-market is that the former has both pre-trade and post-trade transparency while the latter has post-trade transparency only.[14] Pre-trade transparency includes visible bid and ask quotes, quoted volume, and the quoting dealer's identity. Post-trade transparency includes trade price, trade size, time of execution, but no identities. Dealers have the possibility to delay the publication of OTC-trades until the end of the trading day, which means that the trade will not be visible until 4 pm.[15] Trading in the OTC market is mainly conducted over the phone or by electronic messaging. The initiator will ask for a price and will be given a two-way price unless she indicates which direction she is trading. If the initiator accepts the price, the two parties will agree on the trade and should enter the trade details into the OSE trading system within 5 minutes.

4.2 Data

The data set contains all trades in the Norwegian government bond market from September 1999 until November 2012. The 107 300 trades include the identities of the buying and the selling dealer, date, time, price, amount, and whether it is an OTC-trade or an electronic

[14] As the same bonds are traded in the LOB and the OTC-market, the LOB pre-trade transparency contributes to more transparency in the OTC-market for dealers than for customers without direct access to the LOB.

[15] From 1999 to May 2002 the time of delay was 2 hours. Since then delayed trades have been published at 4 pm.

(LOB) trade. The number of bonds outstanding at any time vary between four and six. New eleven year bonds are issued every other year during the sample period and subsequently expanded in the primary market according to a pre-announced auction calendar. A bond will thus reach its final outstanding amount several years after it was first issued. Table 1 displays the characteristics of the ten bonds traded over the period. The first column shows the bond short name while the second and third columns display the year of issuance and year of maturity, respectively. The fourth column displays the number of trades included for each bond and the fifth column shows the share of electronic trades in each bond. Finally, the sixth and seventh columns display the average trade size in million NOK for OTC-trades and electronic trades, respectively. The table reveals that both the share and the average size of trades in the LOB have increased steadily. The average trade size in the OTC-market has remained relatively stable.

(During this period informed dealers had a choice between trading in the LOB or in the OTC-market.[16])

The data set is divided according to trade type (interdealer or customer), trading venue (OTC or LOB), and maturity (short, medium, or long term) of the bonds traded. Interdealer- and customer trades are separated by applying the identity of the buying and the selling dealer. Trades with different buying and selling dealers are defined as interdealer trades, and trades with the same buying and selling dealer are defined as customer trades.[17] The interdealer market constitutes about one fourth of the total bond market measured in trading volume (NOK) and about one third measured in number of trades. Figure 1 displays monthly trading volume in million NOK for all maturities according to trade type and trade venue. The green curve displays customer trading volume of which all trades are executed in the OTC-market. The blue and red curves display interdealer trading volume in the OTC-market and the LOB, respectively. The blue curve reveals that the share of interdealer trading volume in the OTC-market has declined steadily since the inception of the LOB in 1999. In the period 1999 to

[16] In Norwegian government bonds pre-trade transparent limit orders include prices, volume and dealer id, while post-trade transparency includes time of trade, price and volume in NOK.

[17] Brokered trades are also in this category.

2001 about 80 percent of total interdealer trading volume was executed in the OTC-market. This share declined to about 50 percent in the next three to four years. In mid-2005 the share declined further as a result of the termination of the informal quoting agreement. The red curve shows that the trading volume in the LOB has varied substantially over the period with peaks in 2003, 2008, and 2011. In the period from mid-2005 to 2012 the majority of interdealer trading volume has been executed in the LOB.[18]

As the objective of this paper is to study the trade-offs between trading speed and trading cost in dealer markets I employ data on interdealer trades only. The trades of five dealers representing more than 80 percent of total trading volume are used to construct individual order flows. Order flow, which is a measure of buying pressure in the market and a key explanatory variable in this study, is calculated as the daily sum of signed trades. Buyer-initiated trades have a positive sign and seller-initiated trades have a negative sign. Electronic trades executed in the LOB include information on the order sign, while the OTC trades are signed according to the method of Lee and Ready (1991).[19] The paper first employs an order flow measure based on all market orders in both trading venues. Then, to identify the preferred venue and order type for each dealer order flows are split into two parts. One part is the LOB order flow, which is the daily sum of signed initiated trades (market orders) in the LOB. The other part is the OTC order flow, which is the daily sum of signed initiated trades in the OTC-market. In addition the passive order flows in the LOB are calculated for each dealer. The passive order flow reflects a dealer's limit orders that have been hit by other dealers' market orders in the LBO.[20] This order flow measure is constructed such that a positive (negative) passive order flow implies an increase (decrease) in the dealer's inventory of the bonds.

[18]According to some dealers a large share of OTC trades between bond dealers in recent years are related to asset swaps.

[19]The method of Lee and Ready (1991) classifies trades that are executed at a price less than the mid price as seller-initiated, and trades that are executed at a price higher than the mid price as buyer-initiated. For trades executed at the mid price, the tick rule is used. This rule implies that if the price is higher than the previous transaction price (an uptick) it is classified as a buy. If the price is lower (a downtick) it is classified as a sell. If it is unchanged (a zero uptick) the rule is applied to the price that preceded it.

[20]Marketable limit orders are considered as market orders. Marketable limit orders are buy limit orders with a price equal to or above the best ask price or sell limit orders with a price equal to or below the best bid that are exceuted immediately.

The maturity of a bond changes over time and so does the characteristics of the bond. Order flow is therefore divided into three maturity segments according to the remaining time to maturity. Short term order flow includes trades in bonds with a remaining time to maturity from 1 up to 4 years, medium term order flow includes trades in bonds with a remaining time to maturity from 4 years up to 7 years, and long term order flow includes trades in bonds with a remaining time to maturity between 7 and 11 years. Table 2 displays descriptive statistics for the short term, medium term, and long term order flows for each of the five dealers. The table shows that the daily short term order flow of Dealer 1 has a mean around 0, a standard deviation slightly above 1 trade, a minimum of -8 trades, a maximum of 11 trades, and first order autocorrelation of around 10 percent. The following rows present the characteristics of Dealer 1 medium term and long term as well as the characteristics of the three maturity order flows of Dealers 2, 3, 4, and 5.

In addition to order flow data this study employs zero coupon prices and forward rates for Norwegian government bonds. Zero coupon prices are calculated by from end-of-day prices of government bonds and bills using the Nelson-Siegel algorithm.[21] Figure (2) displays that the level of bond yields has varied considerably during the period, from above 7 percent in 2002 to below 2 percent in 2011. The red curve depicts the monetary policy rate which is the deposit (folio) rate at the central bank. The blue, green, and black curves depict the three, five, and ten year government bond yields, respectively. The zero-coupon prices are used to calculate daily excess returns of 1, 2, 3, 5, 7, and 10 year bonds. The descriptives of bond excess returns are reported in Table 2. Mean excess returns and standard deviations are as expected increasing in bond maturity. To control for the predictive power of forward rates, documented by among others Fama and Bliss (1987) and Cochrane and Piazzesi (2005), the first three principal components of one month forward rates 1 to 11 years ahead are also included in the predictive regressions. The first three components are explain 98.8 percent of the total variation in forward rates. The loadings make these three components comparable to the "level", "slope" and "curvature" factors described by Litterman and Scheinkman (1991).

[21] Zero coupon yields and forward rates are kindly provided by Nordea Markets.

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Table 2 further displays the descriptives of the quoted spread based on quotes in the LOB and the effective OTC spread based on OTC trades during the 1999 - 2012 period. The spreads are measured as the difference between the best ask and best bid in percent of the mid-quote in the LOB, and the difference between the trade price in the OTC-market and the mid-quote in in percent of the mid-quote in the LOB, respectively. The table reveals that trading costs in the OTC-market on average are substantially lower than in the LOB. For short term, medium term, and long term bonds the differences are 0.05, 0.09, and 0.14 percent respectively.[23]

Two dummy variables are employed to investigate whether the type of information contained in order flow is fundamental or non-fundamental. The first dummy variable on news days is constructed to investigate whether the information in a dealer's order flow is related to macroeconomic announcements. News days are here as days with the announcement of CPI, retail sales (early indicator for private consumption), and the monetary policy rate and the day after.[24] The day after each news release is also included because interpreting the news and subsequently trading on them may take some time. The second dummy variable on large trades is constructed to investigate whether the information in order flow is related to liquidity. Large trades are defined as trades of 300 mill. NOK or more (40-45 mill.USD).[25] The day after each large trade is also included because the market effects can last for more than a day. The news-dummy includes about 25 percent while the large trade-dummy includes about 40 percent of the trading days.

[22] Litterman and Scheinkman (1991) extract the common factors in Treasury returns and find that the variation in returns on all Treasury fixed income securities can be explained by the three first factors named level, steepness and curvature.

[23] Based on the median spreads the differences are 0.0495, 0.0900, and 0.1215 percent of the mid-quote for short, medium, and long term bonds respectively.

[24] In Norway employment numbers have traditionally not been important movers in financial markets as unemployment rates are relatively low and the government have work schemes making unemployment rates appear very low.

[25] The minimum order sizes has varied between 5 mill.NOK at the inception of the LOB and 50 mill.NOK for the most liquid bond during the period.

5 Information contained in interdealer order flow

5.1 Predictions of bond excess returns based on total order flow

To explore whether any of the dealers trade on information about the future path of bond risk premia I employ bond excess returns as a measure of expected excess returns. The daily excess return of a zero coupon bond with maturity N years is expressed as

$$exr_{t+1}^{(N)} = p_{t+1}^{(N)} - p_t^{(N)} - y_t^{(1m)} . \tag{5}$$

where $exr_{t+1}^{(N)}$ is the excess return on a zero coupon bond with N years to maturity on day t+1, $p_t^{(N)}$and $p_{t+1}^{(N)}$ are the log price of a zero coupon bond with N years to maturity on day t and day t+1, respectively.[26] The one month zero rate, $y_t^{(1m)}$, is employed as the one-period riskless return. Equation (6) states that the actual excess bond return at time t+1 is the one-period bond return minus the one-period riskfree rate at time t.

To investigate whether any of the five dealers possess information about future bond excess returns the following model is employed for excess returns on 1, 2, 3, 5, 7, and 10 year zero coupon bonds:

$$exr_{t+1}^{(N)} = \beta_0 + \sum_{k=1}^{3} \beta_2^k F_t^k + \sum_{i=1}^{5} (\beta_3^i OF_{i,t}^S + \beta_4^i OF_{i,t}^M + \beta_5^i OF_{i,t}^L) + \varepsilon_{t+1}, \tag{6}$$

where $i = 1, 2, 3, 4, 5$ for the five dealers. β_0 is a constant, F_t^k is the k^{th} principal component of forward rates where $k = 1, 2, 3$. Forward rates are included to control for information about future rates already reflected in the yield curve. $OF_{i,t}^S$ is the short term interdealer order flow, $OF_{i,t}^M$ the medium term interdealer order flow, and $OF_{i,t}^L$ the long-term order flow of dealer i on day t based her total trades in the LOB and the OTC-market. ε_{t+1} is the error term. The results of the predictive regressions based on Equation (7) for the period September 1999 to November 2012 are presented in Table 3. The coefficients for the constant and the three

[26]Since the forecasting horizons are short relative to the maturity of the bonds, the excess returns are estimated under the assumption that the remaining time to maturity of the bond is approximately the same at the beginning and at the end of the forecasting period. It is thus assumed that $N\ years - 1\ day \approx N\ years$.

principal components of forward rates are not included in the table to preserve space. The *Adj.* R^2 in each column shows the explanatory power of the model. The bottom row shows the additional explanatory power, $\Delta Adj.\ R^2$, by including the order flow variables.

The results indicate that the predictive power of interdealer order flows vary between dealers, order flow maturity groups, and at which points of the yield curve we measure excess returns. The medium term order flow of Dealer 1, the medium term order flow of Dealer 3, and the short term order flow of Dealer 4 have predictive power for excess returns on three year bonds. All five dealers have one maturity order flow with predictive power for 5 year excess returns, and Dealer 1 medium term order flow, Dealer 2 long term order flow, and Dealer 3 medium term order flow all have predictive power at the 5 percent level or better. An increase in Dealer 3 medium term order flow by one (0.67) trade predicts an increase in the next day five year excess return of 2.2 (1.5) basis points. Three dealers have order flows that can predict 10 year excess returns. Dealer 4 long term order flow has the strongest predictive power where an increase by one (0.82) trade predicts an increase of 3.9 (3.23) basis points in excess returns. The results in Table 3 show that adding order flow variables to the model increases the *Adj.* R^2 by up to 1.9 percentage points and that all dealers order flows contain at least some information relevant for future bond excess returns.

To evaluate the predictability of order flows over time and identify periods when a dealer possess private information I follow the method of Goyal and Welch (2008). I estimate out-of-sample recursive forecasts of each dealer's order flow and compare them to naive forecasts based on average past excess returns. As uninformed investors are likely to base their expectations on past realized excess returns, this comparison should reveal whether a dealer's order flow contains private information about future excess returns or not. A positive slope indicates that the accumulated MSE of the order flow model is smaller than the accumulated MSE of the naive model and suggests that the dealer possess private information. A flat or negative slope indicates that the accumulated MSE of the order flow model is the same or larger than the accumulated MSE of the naive model and suggests that the dealer do not possess private information.

Figure 3, based on the Goyal and Welch (2008) method, illustrates the out-of-sample predictive power of all dealers' order flow on excess returns on five year bonds from September 2000 to November 2012. The black line shows the performance of Dealer 1 medium term order flow, the light blue line Dealer 2 long term order flow, the dark blue line Dealer 3 medium term order flow, the red line Dealer 4 long term order flow, and the green line Dealer 5 short term order flow against the naive benchmark model. The figure reveals that the predictive power of the order flow models not only vary substantially across dealers, but also vary substantially over time. The order flow models of Dealers 3, 4, and 5 perform best relative to the naive forecast up to 2005. The Dealer 1 order flow model does particularly well after the onset of the financial crisis in 2008. The Dealer 2 order flow model, however, is outperformed by the naive model for most of the period except at the very end of the period.

5.2 Predictions based on OTC order flow, LOB order flow, and passive order flow

The results in the previous section reveal that there is some private information in bond dealers' market orders. In this section order flow is split into OTC order flow and LOB order flow. In addition, "passive" order flow, which reflects a dealer's trades in the LOB initiated by other dealers, is employed. With these three order flow measures this section explores the preferred trading strategy of informed dealers; market orders in the LOB, limit orders in the LOB, or market orders in the OTC-market.

If dealers systematically prefer one of the first three trading strategies presented above, there should be a difference in the predictive power of the three order flow measures. The following model is employed to investigate the predictive power of LOB order flow and OTC order flow separately,

$$exr_{t+1}^{(N)} = \beta_0 + \sum_{k=1}^{3} \beta_2^k F_t^k + \sum_{i=1}^{5} \sum_{d=S}^{L} (\beta_{3,d}^i OFB_{i,t}^d) + \sum_{i=1}^{5} \sum_{d=S}^{L} (\beta_{4,d}^i OFO_{i,t}^d) + \epsilon_{t+1}, \qquad (7)$$

where OFB_i^d and OFO_i^d represent Dealer i's order flows in the LOB and the OTC-market respectively for the three maturity groups $d = S, M, L$. The model presented in Equation (8) is run for the period 1999 to mid-2005. During this period dealers agreed to quote to each other in the OTC- market and Figure 1 shows that trading volume was substantial in both venues. The model is subsequently run for the whole period including LOB-order flow only.

The results are presented in Table 4. The first three columns display the results for 3-, 5-, and 10-year bond excess returns for the 1999-2005 period, and the last three columns the same returns for the whole period. The results in the three first columns reveal that only LOB order flows have predictive power. The only exception is Dealer 2 medium term OTC order flow which has predictive power at the 10 percent level for 3- and 5-year excess returns. The results further show that Dealer 1 order flows have no predictive power during this period. Dealer 3 medium term and Dealer 5 short and medium term order flow have predictive power for 3- and 5-year bonds. Dealer 2 long term order flow has predictive power for all bond maturities while Dealer 4 long term order flow has predictive power for long bonds only.

The results in last three columns confirm the predictive power of the dealers' LOB order flow and reveal that also Dealer 1 order flow has predictive power for the period as a whole. While Dealer 1 medium term and Dealer 2 long term order flow predict excess returns along the whole yield curve, the order flows of the remaining dealers predict better at specific parts of the yield curve. The adjusted R^2s are somewhat higher than in Table 3 adding to the evidence that informed dealers prefer the LOB to the OTC-market.

Finally, to investigate whether informed traders use limit orders, as suggested by Kaniel and Liu (2006), the following model is employed for the whole 1999 to 2012 period,

$$exr_{t+1}^{(N)} = \beta_0 + \sum_{k=1}^{3} \beta_2^k F_t^k + \sum_{i=1}^{5} (\beta_3^i POFB_{i,t}^S + \beta_4^i POFB_{i,t}^M + \beta_5^i POFB_{i,t}^L) + e_{t+1}, \qquad (8)$$

where $POFB_i^S$, $POFB_i^M$, and $POFB_i^L$ represents Dealer i's short, medium, and long term passive order flow in the LOB. When Dealer i's passive order flow is positive (negative) she is a net buyer (seller) of bonds from other dealers. This reflects that Dealer i's counterparties have submitted more sell (buy) market orders than buy (sell) market orders.

Table 5 presents the results of the model. Three of the five dealers have passive order flows with predictive power. Dealer 2 passive order flows in all maturity groups are significant at the 5 percent level or better along the whole yield curve. Dealer 1 and Dealer 4 passive order flows are significant for long term bonds and medium term bonds, respectively. However, note that the signs of the significant coefficients are all negative. This is the opposite of the findings in Table 3 and Table 4 where the signs are positive. Negative coefficients indicate that net buying (selling) of bonds through limit orders predicts a fall (increase) in next day excess returns. This implies a loss for the dealer posting the limit order and a profit for the dealer initiating the trade. The source of predictive power of passive order flow thus appears to be the private information possessed by the initiating dealers, not the posting dealers. The predictive power of Dealer i's passive order flow thus depends on the information of her counterparties. As market orders are executed at the best quotes available, the passive order flow of dealers posting the most competitive limit orders will have the highest predictive power.

To examine informed dealers' choice of trading venue and order type over time I make separate out-of-sample forecasts for the three types of order flow. Again, the framework of Goyal and Welch (2008) is employed. Figures 5 to 9 illustrate the predictive power of the three types of order flows for each of the five dealers. The solid curve shows the performance of the LOB order flow model, the dotted curve the OTC order flow model, and the dashed curve the passive order flow model against the naive model. The maturity segments employed in the figures represent the most informed segment for each dealer based on the in-sample predictions in Table 4. An increase in any of the curves means that the particular order flow model outperforms the naive model and suggests that the dealer uses this venue when she is trading on information.

Figure 5 illustrates the predictive power of Dealer 1 medium term LOB order flow, OTC order flow, and passive order flow on next day excess returns on five year bonds. The upward sloping solid curve shows that Dealer 1 medium term order flow in the LOB outperforms the naive model for short periods in 2001 and 2003 and again for the entire period after the financial crisis. The dotted curve, reflecting predictions based on OTC order flow, is flat and slightly below zero both before and after mid-2005. This indicates that while there is some information about future excess returns in Dealer 1's LOB market orders, there is no such information in her OTC market orders. The dashed line, reflecting predictions based on passive order flow, is below zero and unable to outperform the naive model for most of the sample period, except at the very end. The increase in 2012 indicates that Dealer 1 passive order flow in medium term bonds contains some information during this period. Based on the results in Table 5, this is likely to reflect the information of Dealer 1's counterparties in the LOB.

Figure 6 illustrates the predictive power of Dealer 2 long term LOB order flow, OTC order flow, and passive order flow on next day excess returns on ten year bonds. The solid curve is below zero for most of the period with the exception of 2012 and indicates that the LOB order flow model is outperformed by the naive model. The dotted line is almost flat just below zero indicating no predictive information in OTC order flow. However, the dashed line, reflecting predictions based on passive order flow, is positive and mostly increasing over the whole period. The predictive information appears to belong to the counterparties of Dealer 2 since the coefficient in Table 5 is negative. The superior performance of this order flow model indicates that Dealer 2 provides the best limit orders when other dealers possess information.

Figure 7 illustrates the predictive power of Dealer 3 medium term LOB order flow, OTC order flow, and passive order flow on next day excess returns on five year bonds. The solid curve is increasing through 2003 and 2004 clearly indicating that Dealer 3's LOB order flow contains information about future excess returns. From 2005 to the end of 2011 the curve is slightly decreasing indicating that Dealer 3 order flow contains little information and that forecasts based on the naive model predict better. At the end of 2011 the information content in Dealer 3 LOB order flow is increasing again. The dotted curve, reflecting OTC order flow, increases slightly in 2003, and is then flat close to zero the rest of the period. The dashed curve, reflecting passive order flow, is below zero for most of the period. It contains some predictive power for a brief period in 2003 and at the end of the period.

Figure 8 illustrates the predictive power of Dealer 4 long term LOB order flow, OTC order flow, and passive order flow on next day excess returns on ten year bonds. The positive slope of the solid line shows that the LOB order flow model has predictive power for ten year excess returns and clearly outperforms the naive model. The model did particularly well during the 2002-2004 period and the 2008-2010 period. The dotted line, representing OTC order flow, indicates that OTC long term order flow has some predictive power during the 2001-2003 period. The dashed curve is negative to about 2008 and then positive and strongly increasing after that. The negative sign from the in-sample prediction indicates that Dealer 4's counterparties in the LOB are trading on private information from this time and especially from 2010.

Finally, Figure 9 illustrates the predictive power of Dealer 5 medium term LOB order flow, OTC order flow, and passive order flow on excess returns on five year bonds. The solid curve shows that the LOB order flow model clearly outperforms the naive model in the period up mid-2005. Except for a short period at the end of 2008, Dealer 5 medium term LOB order flow has no predictive power thereafter. OTC order flow has some predictive power in 2000 to 2001, but is outperformed by the naive model for the rest of the time. The declining dashed line reveals that the model based on Dealer 5 passive order flow is clearly outperformed by the naive model, and indicates that informed dealers do not trade on this dealer's limit orders.

In all, the results from the in-sample and out-of-sample predictions based on the three order flow measures in this section suggest that the predictive power found in the previous section originates from market orders in the LOB. Despite the larger average size of OTC trades, OTC order flow has virtually no predictive power. Dealers 3, 4, and 5 appear to be best informed during the period up to mid-2005. For the whole period Dealers 1, 3, and 4 appear to be best informed. Dealer 2 appears to be less informed than the other dealers. Finally, the information in passive order flow appears to originate from the dealers hitting limit orders, not from the dealers posting them. The strong predictive ability of Dealer 2 passive order flow combined with little predictive power of Dealer 2 LOB and OTC order flow points to a tendency of less informed dealers providing liquidity to better informed dealers. However, from 2011 it appears that informed dealers provide liquidity to informed dealers as both LOB order flow and passive order flow have predictive power for many dealers. This could be related to the fact that the number of primary dealers was reduced from six to four during 2011.

5.3 The trade-off between speed, cost and execution risk

The results in the previous section reveal that dealers in the Norwegian government bond market prefer trading in the LOB rather than in the OTC-market when they possess information about future bond excess returns. They also prefer market orders to limit orders. Why do informed dealers prefer speed at the expense of lower trading costs, and shun execution risk? According to the framework presented above it indicates that the total trading costs in the OTC market are higher than the quoted half spread and that the decay costs related to limit orders in the LOB are higher than the quoted spread.

The three models depicted in each of Figures 7 to 11 represent the three basic trading strategies available to each dealer. The first trading strategy, market orders in the LOB, involves no decay costs. The second trading strategy, market orders in the OTC-market, can have decay costs. Sometimes bond prices can change from the time the decision to trade is made to the time another dealer bilaterally announces a quote. Also, as there is no pre-trade transparency in the OTC-market the initiating dealer may expect a better price or lower spread than the current dealer is quoting. If the initiating dealer passes on the trade and contacts a new dealer the price can change in the meanwhile to the disfavor of the initiating dealer as other informed dealers are trading. The third trading strategy, posting limit orders in the LOB, have decay costs. These costs can be potentially large. Even if an informed dealer posts a limit order within the current quoted spread it may not be executed. If other dealers believe the limit order contains information they will change their quotes accordingly and the market will move away from the informed dealer's limit order. This reduces the probability of execution at the posted price. If the dealer has to post a new limit order to obtain execution she can end up with an unfavorable price implying a large slippage cost.

Table 7 illustrates the differences in trading costs as measured by the spreads in the LOB and the OTC-market for the period 1999-2005. The table reveals that on average trading costs for dealers are 3 to 7 basis points higher in the LOB than in the OTC-market. While trading costs on average are lowest for dealers in the OTC-market, the variation in trading costs is highest. The fourth column shows that the standard deviation increases with bond maturity as expected. However, it also differs significantly for same maturity bonds across venue and trader type.[27] The standard deviation is lowest for quoted spreads in the LOB, somewhat higher for customer OTC-spreads, and highest for interdealer OTC-spreads.[28] While the OTC-spread on long bonds for dealers has a standard deviation that is 88 percent higher than the standard deviation of the LOB-spread on long bonds, the corresponding difference for customers is only 12 percent higher.

Table 7 is compatible with the view that it is difficult for dealers to hide information in a market with relatively few central dealers. A higher OTC spread than normal and a slippage cost due to a leakage of information is a possible reason for informed dealers preferring markets orders in the LOB. The differences in customer and dealer spreads in the OTC-market can reflect that in this type of dealer market dealers need to maintain a good relationship and will normally offer each other low or even no spreads on uninformed trades. However, if a liquidity providing dealer encounters a dealer possessing private information she will quoting a large, or skewed spread, thus the high standard deviation for this type of trades.

5.4 Types of information

Another possible reason for informed dealers preferring markets orders in the LOB is that private information is short-lived. Kaniel and Lui (2006) find that stock traders at the NYSE prefer market orders if information is short-lived and limit orders if information is long-lived. They define short-lived information as having a horizon of one hour and long-lived information as having a horizon of one day. For dealers in government bonds possible sources of private information are superior interpretation of macroeconomic news and large customer trades related to hedging or speculation. Considering these two examples it seems reasonable to

[27] Tests of equality of variances between series (Bartlett F-test, Siegel-Tukey, Levene, and Brown-Forsythe) confirm that standard deviations across venue, trader type, and bond maturity are significantly different from each other.

[28] The lower variation in quoted LOB spreads can be related to primary dealer regulations governing maximum quoted spreads.

assume that fundamental information based on macroeconomic news has a longer horizon than non-fundamental information about a large customer trade.

I employ two dummy variables to investigate whether the information in a dealer's order flow can be related to either of the two types of private information. The first dummy includes main macroeconomic announcements in Norway and the second includes days with large customer trades.[29] I use the following model,

$$exr_{t+1}^{(N)} = \beta_0+\sum_{k=1}^{3}\beta_2^k F_t^k+\sum_{i=1}^{5}(\beta_3^i OF_{i,t}^S*D_{news,t}+\beta_4^i OF_{i,t}^M*D_{news,t}+\beta_5^i OF_{i,t}^L*D_{news,t})+\varepsilon_t, \quad (9)$$

where $Abs(OFM_{i,t}^{m,d})$ is the absolute value of Dealer i's order flow in market m where $m = LOB, OTC$, and maturity group $d = S,\ M,\ L$. D_{news} is the dummy for news days, and $D_{bigtrade}$ is the dummy for large trade days. Table 7 reports the results for the period 1999 to mid-2005 in the first three columns and for the period mid-2005 to 2012 in the last three columns. The first and fourth columns show the effect of news days, the second and fifth the effect of large trade days, and the third and sixth columns show the adjusted $R^{2\prime}s$. The table reveals that for the first period news-days, and not large-trade-days, have a significant effect on LOB order flows. During the same period OTC order flows appear to be affected by both macroeconomic news and large trades. For the 1999 to 2012 period the picture is mixed and reveals substantial differences between the five dealers.

Dealer 1 has more one-sided trading in the LOB on news-days during the first period. During the same period OTC-market order flows are affected on news-days as well as on large-trade-days. For the whole period LOB order flow appears to be more one-sided on large-trade-days. This finding combined with the results in Table 4 is consistent with Dealer 1 medium term LOB order flow containing predictive non-fundamental information related to large orders and liquidity. Dealer 2 is the only dealer with LOB order flows being unrelated to news-days in the first period. During the same period OTC-market order flows are affected on news-days as well as on large-trade-days. For the whole period Dealer 2 LOB order flows

[29] Both dummies include the news/large trade day and the following day.

are related to large-trade-days only. Combined with the results in Table 4 this is consistent with Dealer 2 long term LOB order flow containing predictive non-fundamental information related to large orders and liquidity.

Dealer 3 has more one-sided trading in both the LOB and the OTC-market on news-days as well as large-trade-days during the first period. When considering the whole period, however, the absolute value of Dealer 3 order flow is higher on news days only. This finding combined with the results in Table 4 is consistent Dealer 3 medium term LOB order flow containing superior interpretations of macroeconomic news. Dealer 4 order flows appear to be little related to the two dummy variables. During the first period short term order flow in both venues are more one-sided on news-days, but for the whole period Dealer 4 order flows appear to be unrelated to news-days and large-trade-days. This, combined with the results in Table 4 is consistent with Dealer 4 long term LOB order flow containing some other type of predictive private information. Such information could be related to international macro news or other factors not covered by the two dummy variables. Finally, Table 7 shows that Dealer 5 order flows in both venues and both periods are more one-sided on news-days. This, combined with the results in Table 4 and the steep slope of the solid line in Figure (8) up to 2005 is consistent with Dealer 5 medium term LOB order flow containing superior interpretations of macroeconomic news. Dealer 5 appears to maintain this superior ability to predict future bond excess returns up to 2005.

By comparing Figures (5) to (9) to Figure (2) which displays changes in the monetary policy rate it appears that periods of high predictability for some dealers coincide with periods of monetary policy changes. The monetary policy rate was cut in December 2001 as a response to the economic downturn after 9/11. The Norwegian central bank then increased the monetary policy rate from 6.50 percent to 7.00 percent in July 2002 after an expensive wage settlement fearing higher inflation.[30] This increase came as a surprise to many market participants. After a sharp decline in the inflation rate to below the 2.5 percent target in the fall of 2002 the central bank started a long cycle of cutting rates in December 2002. The

[30] I Norway wages for large groups of employees are determined centrally by the major labor unions and employer organizations every other year.

monetary policy rate declined from 6.50 percent in December 2002 to 1.75 percent in March 2004. After a tightening cycle from mid 2005 to mid 2008 the monetary policy rate was reduced from 5.75 percent in September 2008 to 1.50 percent in 2012.

Figure (7) shows that the Dealer 3 medium order flow model predicts particularly well in 2003/2004. The central bank was cutting the policy rate by 100 basis points at two consecutive meetings in the summer of 2003 and continued lowering in the next few months. The Dealer 5 medium order flow model predicts well for a long period from late 2001 to end 2005. Figure (9) shows that only for a brief period in the summer of 2003 did the Dealer 5 order flow model underperform relative to the naive model. These findings are consistent with Dealer 3 and Dealer 5 possessing fundamental private information generated by superior analytical teams.

The results of the investigation in this section suggest that the predictive power of the Dealer 1 medium term and the Dealer 2 long order flow model for 2011/2012 are related to effects of large trades. This is consistent with Dealer 1 competing for customer order flow to obtain information and following the flows in the market closely. Dealer 2 appears to act more like a pure market maker than the other dealers. In all, the results in this paper indicate that private information held by the five bond dealers can be short-lived or difficult to hide and thus is exposed to slippage unless market orders in the LOB are chosen.

6 Conclusion

Regulators are proposing new pre-trade transparency requirements in bond markets currently organized as OTC-markets. The reforms are proposed to improve market quality including the speed of price discovery process. This paper investigates whether the introduction of a transparent limit order book in a former OTC bond market is likely to move the price discovery process on to the lit venue and thus increase the informativeness of bond prices. The results, based on data from the Norwegian government bond market, suggests that this is the case when the LOB is regulated by imposing maximum spreads and minimum volume. Informed dealers prefer to use market orders in the limit order book. Pre-trade transparent limit orders and trade prices published immedialtely after the trade is executed will reflect the fundamental value of the bonds faster than in an OTC-market where past trade prices are visible with a delay. However, quoted, tradable spreads in a market with infrequent trading will be high due to high trading costs

These include the corporate bond market, the agency bond market,the municipal bond market, and the off-the-run Treasury market. This paper sheds light on the effects of pre-trade transparency on informed trading by documenting the trade-offs between speed, trading cost, and execution risk in the interdealer market for Norwegian government bonds. This market introduced electronic trading in 1999 and the LOB and the OTC-market existed alongside until 2005 when a voluntary quoting agreement was terminated and OTC-trading volume fell substantially. The paper investigates the information content of LOB order flow, OTC order flow and passive LOB order flow for five heterogeneously informed dealers to reveal which venue and order type they choose when trading on information. Informed dealers are defined as dealers whose order flow contains information about future bond excess returns. Specifically, their information is of a character such that their interdealer order flow predicts bond excess returns with a positive coefficient.

The results from the complete trading records of the five dealers document that informed dealers choose markets orders in the LOB. The preference for immediate trade execution is likely to reflect that information is short-lived or difficult to hide and thus is exposed to an erosion over time due to the competition from (near) future informed dealers. The difficulty of hiding private information in dealer markets with few central dealers expose informed market orders in the OTC-market to higher spreads and slippage costs. Slippage costs may arise as a dealer is waiting for a quote from one or more liquidity providing dealers. The results suggest that the total costs for an OTC-trade are higher than the total costs for a market order in the LOB. This indicates that the introduction of pre-trade transparency will be welcomed by informed dealers.

The strong preference of market orders to limit orders trading can reflect the low trading frequency, which is typical for many bond markets. A slippage cost related to limit orders can be interpreted as an endogenous waiting cost as the informed traders' expected payoffs decreases gradually over time. The longer waiting time, the larger waiting cost for the informed. Also, slippage costs are increasing in the mispricing in the market which is likely to be higher in less liquid bond markets. Private information related to fundamental as well as non-fundamental news can potentially imply a high mispricing and thus a high slippage cost. A slippage cost above the spread in the LOB indicates that the preferred trading strategy of an informed dealer is a market order. This is in line with Menkveld et a. (2014) who find that the preferred transparency level increases with the urgency of the trader. The more urgent, the more transparent trading venue is chosen.

The preference for speed can reflect that limit orders and negotiations in OTC markets are exposed to waiting costs resulting in a "slippage" of their information advantage. This erosion in information advantage is important in markets where trade frequency is low and private information is difficult to hide.

The results further show that even if informed dealers prefer market orders, there is information in a dealer's limit orders. However, the information belongs to this dealer's counterparty who uses a market order. I find that less informed dealers tend to provide liquidity to better informed dealers in the LOB. (This is in line with the equilibrium derived in Foucault, Kadan, and Kandel (2005) which is that patient traders tend to provide liquidity to less patient traders. (The optimal order placement strategies depend on the expected waiting time function and waiting cost per unit of time.)This is likely a result of the market-making obligations of primary dealers. The preferences of informed traders in the Norwegian government bond market suggest that the introduction of pre-trade transparency for bonds currently trading in OTC-markets should be coupled with the establishment of designated market-makers to secure liquidity provision and prevent trading volume from falling.

6.1 Appendix

To compare the out-of-sample performance of the order flow models with the benchmark, the mean squared forecasting errors (MSE) of the recursive forecasts from the two models presented in Equation (8) and Equation (9) are calculated.

To test whether the MSE of the order flow model is significantly smaller than the MSE of the naive model, the McCracken (2007) MSE-F test is employed. This test statistic tests the null hypothesis that the naive constant excess return model has a MSE that is less than or equal to that of the time varying excess return model. The alternative hypothesis is that the time-varying model has a lower MSE. The test statistic is

$$MSE - F = (T - h + 1) * (\frac{MSE_R - MSE_U}{MSE_U}), \tag{10}$$

where T is the number of observations in the sample, h is the horizon, MSE_R is the mean squared forecast error of the naive model and MSE_U is the mean squared forecast error of the order flow model. Equation (11) defines the test statistic as the ratio of the difference in the two MSEs over the MSE of the order flow model being evaluated times the number of observations. Critical values of this non-standard test are provided in Clark and McCracken (2005). Table 5 presents the out-of-sample results for three, five, and ten year excess returns. The first column shows the maturity of the bond while the second and third columns show which dealer and which order flow maturity group is included in the alternative order flow model. The fourth column reports the ratio of the accumulated mean squared errors (MSE) between the two models and the fifth column reports the result of the MSE-F test. The results show that Dealer 1 and Dealer 3 medium term order flow, and Dealer 4 long term order flow have the strongest predictive power for next day excess returns for three to ten year bonds over the period 2000 - 2012.

Goyal and Welch (2008) test the stability of a range of predictive variables and monitor the predictive power of these variables relative to a naive benchmark over the whole sample period. They do this by illustrating graphically the cumulative squared prediction errors of the naive model minus the squared prediction errors of the alternative order flow model.

Peak of the European sovereign debt crisis was August 2011 to March 2012.

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Table 1: Benchmark bonds

The bonds included in the data set are all bullet bonds with a remaining time to maturity of ten or eleven years when first issued. The table displays the bond short name, the year issued, the year of maturity, the number of ordinary trades in each bond , the share of electronic trades in the LOB, the average trade size of OTC trades and LOB trades, and the number of repos divided into repos that are part of the central bank securities lending program and market repos that are interdealer or between dealers and customers. All transactions are reported to Oslo Stock Exchange (OSE) from September 6, 1999 to November 8, 2012. Ordinary trades and repos in bonds with less than 12 months until maturity are not included. The share of LOB trades are measured as the number of LOB trades as a percentage of the total number of trades in each bond. Average trade size is measured in million Norwegian kroner (NOK)

Bond name	Issued year	Maturity year	Number of trades	Share (%) LOB	Avg. trade size OTC	Avg. trade size LOB
S463	1992	2002	6,088	14.1	51.6	9.3
S465	1993	2004	14,366	16.7	34.8	13.7
S467	1996	2007	15,993	24.0	36.2	16.0
S468	1998	2009	19,886	19.9	37.1	14.7
S469	2000	2011	17,272	22.5	43.9	16.4
S470	2002	2013	12,776	26.9	60.6	19.4
S471	2004	2015	9,031	21.8	57.6	24.1
S472	2006	2017	5,730	32.7	59.8	25.0
S473	2008	2019	3,577	45.0	65.1	22.3
S474	2010	2021	2,581	37.6	58.8	22.4
All			107,300	23.1	48.5	18.3

Table 2
Dealers characteristics

The table shows the average market shares of each dealer from 1999 to 2012. The market shares in first nine rows are based on interdealer trades while the market shares in the last three rows are based on customer trades (between a dealer and a non-exchange member) The three first rows display the market shares for active (initiated) trading volume (NOK) in the LOB. The next three rows display the market shares for passive (limit orders hit by another dealer) trading volume (NOK) in the LOB. The last three rows based on interdealer trades display the market shares for active trading volume (NOK) in the OTC market from 1999 to mid-2005. Finally, the last thee rows of the table display the market shares of customer trading volume in the OTC-market. Market shares are in percent of the total trading volume for the five dealers in each market segment.

Interdealer market shares:	Dealer 1	Dealer 2	Dealer 3	Dealer 4	Dealer 5
LOB (active)					
Short	27.3	21.5	16.8	19.4	15.1
Medium	28.0	23.1	15.4	19.6	14.0
Long	27.6	22.6	16.4	21.6	11.8
LOB (passive)					
Short	25.4	27.1	14.7	20.4	12.4
Medium	25.5	30.0	13.7	20.3	10.5
Long	26.2	28.2	14.4	20.8	10.5
OTC (99-05)					
Short	30.0	21.1	22.5	21.2	5.7
Medium	28.3	19.4	19.3	21.2	11.7
Long	28.8	21.3	23.2	17.6	9.1
Customer market shares:					
Short	24.4	25.0	20.0	21.7	8.8
Medium	24.4	25.8	20.5	19.9	9.4
Long	22.7	24.1	23.1	20.7	9.5
Relative quoted spreads:					
Short	0.1812	0.1779	0.1924	0.1777	0.1847
	(0.153)	(0.062)	(0.246)	(0.071)	(0.073)
Medium	0.2814	0.2985	0.2946	0.2854	0.2897
	(0.073)	(0.085)	(0.127)	(0.084)	(0.121)
Long	0.3992	0.3882	0.3917	0.3699	0.3850
	(0.524)	(0.098)	(0.185)	(0.083)	(0.169)
Relative effective spreads:					
Short	0.0645	0.0777	0.0601	0.0743	0.0650
	(0.043)	(0.058)	(0.050)	(0.059)	(0.078)
Medium	0.1067	0.1077	0.0928	0.1086	0.0930
	(0.079)	(0.073)	(0.073)	(0.080)	(0.071)
Long	0.1344	0.1348	0.1412	0.1438	0.1422
	(0.113)	(0.094)	(0.115)	(0.136)	(0.139)

Table 3

Descriptive statistics for daily bond market and order flow variables

The table presents the descriptive statistics for the five dealers' interdealer order flow in short, medium, and long term bonds, daily excess returns in 1, 2, 3, 5, 7 and 10 year zero coupon bonds, and quoted and effective spreads for bonds in the three maturity groups over the period September 1999 to November 2012. The last column displays the first order autocorrelation for the variables.

Series	obs	mean	std.dev.	minimum	maximum	AR(1)
OF_1^S	3310	0.018	1.033	−8.0	11.0	0.106
OF_1^M	3310	0.066	1.056	−11.5	15.0	0.068
OF_1^L	3310	−0.017	1.091	−10.0	10.0	0.059
OF_2^S	3310	−0.083	0.787	−10.0	6.5	0.095
OF_2^M	3310	−0.050	0.719	−6.0	7.0	0.073
OF_2^L	3310	−0.066	0.731	−6.0	7.0	0.149
OF_3^S	3310	−0.038	0.784	−15.0	6.0	0.105
OF_3^M	3310	0.027	0.668	−7.5	7.0	0.059
OF_3^L	3310	−0.017	0.796	−9.0	12.0	0.057
OF_4^S	3310	0.013	0.729	−7.0	12.0	0.075
OF_4^M	3310	0.040	0.739	−7.0	8.0	0.058
OF_4^L	3310	−0.016	0.819	−7.0	9.0	0.052
OF_5^S	3310	−0.079	0.843	−25.0	7.0	0.157
OF_5^M	3310	−0.015	0.722	−13.0	6.0	0.035
OF_5^L	3310	−0.040	0.604	−7.0	8.0	0.035
exr1	3310	−0.0092	0.0432	−0.2504	0.6461	0.125
exr2	3310	−0.0080	0.0885	−0.5109	0.9465	0.165
exr3	3310	−0.0067	0.1477	−0.7894	1.2526	0.143
exr5	3310	−0.0043	0.2466	−1.6351	1.9857	0.159
exr7	3310	−0.0019	0.3291	−1.7928	2.2433	0.163
exr10	3310	0.0013	0.4388	−2.4293	2.4693	0.150
$qspr^S$	3310	0.1316	0.0682	0.0000	1.6659	0.836
$qspr^M$	3310	0.2152	0.1040	0.0000	2.8894	0.841
$qspr^L$	3294	0.3011	0.1466	0.0000	4.0948	0.841
$effspr^S$	3211	0.0771	0.0511	0.0000	1.0197	0.446
$effspr^M$	3119	0.1208	0.0772	0.0000	0.8829	0.408
$effspr^L$	3031	0.1658	0.1116	0.0000	1.5038	0.414

Table 4

Response of daily bond excess returns to individual interdealer order flow

The table presents the results of the following model over the period 1999-2012,

$$exr_{t+1}^{(N)} = \beta_0 + \sum_{k=1}^{3} \beta_2^k F_t^k + \sum_{i=1}^{5} (\beta_3^i OF_{i,t}^S + \beta_4^i OF_{i,t}^M + \beta_5^i OF_{i,t}^L) + \varepsilon_{t+1},$$

where $exr_{t+1}^{(N)}$ is the excess return of a N-year zero coupon bond, where $N = 1, 2, 3, 5, 7, 10$. $OF_{d,t}^S$, $OF_{d,t}^M$, and $OF_{d,t}^L$ are the short-, medium-, and long-term interdealer order flow of Dealer d where $d = 1, 2, 3, 4, 5$. Order flow is measured as the sum of the signed number of trades on both venues per day. The regressions include a constant and the lagged three first principal components of forward rates. $\Delta Adj.R^2$ displays the additional predictive power by adding the order flow variables. Coefficients are in basis points (0.01 percentage points) and corrected for autocorrelation and heteroscedasticity by the Newey-West method. Coefficients in bold are significant at the 10% level or better and an asterisk indicates that the coefficient is significant at the 5% level or better. T-statisics are in parentheses.

	$exr_{t+1}^{(1Y)}$	$exr_{t+1}^{(2Y)}$	$exr_{t+1}^{(3Y)}$	$exr_{t+1}^{(5Y)}$	$exr_{t+1}^{(7Y)}$	$exr_{t+1}^{(10Y)}$
$OF_{1,t}^S$	**0.21***	0.24	0.23	−0.05	−0.38	−0.72
	(2.54)	(1.43)	(0.76)	(−0.11)	(−0.54)	(−0.75)
$OF_{1,t}^M$	0.01	0.25	**0.57***	**1.40***	**1.79***	**1.95***
	(0.21)	(1.59)	(2.18)	(3.03)	(3.08)	(2.43)
$OF_{1,t}^L$	0.02	0.07	0.31	0.73	1.11	**1.68**
	(0.31)	(0.45)	(1.09)	(1.53)	(1.64)	(1.85)
$OF_{2,t}^S$	0.11	0.34	0.62	0.95	**1.61**	1.90
	(0.75)	(1.15)	(1.38)	(1.35)	(1.71)	(1.48)
$OF_{2,t}^M$	0.12	0.29	0.57	0.90	1.40	1.63
	(1.11)	(1.31)	(1.47)	(1.47)	(1.59)	(1.34)
$OF_{2,t}^L$	0.09	0.24	0.58	**1.39***	**2.45***	**3.28***
	(0.91)	(1.10)	(1.61)	(2.27)	(2.92)	(2.86)
$OF_{3,t}^S$	**0.31***	0.41	0.45	0.55	−0.11	−0.51
	(2.18)	(1.59)	(1.14)	(0.84)	(−0.13)	(−0.57)
$OF_{3,t}^M$	**0.25**	**0.67***	**1.06***	**1.53***	1.32	0.91
	(1.70)	(2.37)	(2.43)	(2.03)	(1.37)	(0.70)
$OF_{3,t}^L$	0.02	0.13	0.17	0.81	1.28	1.66
	(0.19)	(0.63)	(0.49)	(1.38)	(1.56)	(1.35)
$OF_{4,t}^S$	0.09	**0.46***	**0.84***	0.71	0.82	0.67
	(0.89)	(2.22)	(2.26)	(1.22)	(0.92)	(0.56)
$OF_{4,t}^M$	0.15	0.14	0.20	0.87	1.10	1.19
	(1.43)	(0.67)	(0.53)	(1.34)	(1.24)	(1.10)
$OF_{4,t}^L$	0.08	0.18	0.38	**1.06**	**2.09***	**3.23***
	(0.88)	(0.93)	(1.14)	(1.85)	(2.77)	(3.17)
$OF_{5,t}^S$	**0.16***	**0.36***	**0.53**	**0.86**	0.93	0.98
	(2.06)	(2.04)	(1.73)	(1.93)	(1.60)	(1.07)
$OF_{5,t}^M$	0.10	0.18	0.24	0.71	0.62	0.92
	(0.94)	(0.73)	(0.59)	(0.99)	(0.58)	(0.62)
$OF_{5,t}^L$	0.03	−0.03	−0.13	−0.55	−1.00	−1.55
	(0.15)	(−0.07)	(−0.08)	(−0.47)	(−0.65)	(−0.87)
$Adj.R^2$	0.0323	0.0167	0.0145	0.0181	0.0197	0.0171
$\Delta Adj.R^2$	0.0108	0.0128	0.0137	0.0176	0.0189	0.0161

Table 5

The table presents the results of the following model over the period 1999-2012,

$$exr_{t+1}^{(N)} = \beta_0 + \sum_{k=1}^{3} \beta_2^k F_t^k + \sum_{i=1}^{5} (\beta_3^i COF_{i,t}^S + \beta_4^i COF_{i,t}^M + \beta_5^i COF_{i,t}^L) + \varepsilon_{t+1},$$

	$exr_{t+1}^{(3Y)}$	$exr_{t+1}^{(5Y)}$	$exr_{t+1}^{(10Y)}$
$COF_{1,t}^S$	0.31 (1.25)	0.30 (0.74)	−0.10 (−0.75)
$COF_{1,t}^M$	**0.58** (1.85)	**1.31*** (2.50)	**1.59** (1.75)
$COF_{1,t}^L$	0.43 (1.43)	**1.22*** (2.28)	**1.88** (1.89)
$COF_{2,t}^S$	0.05 (0.25)	−0.18 (−0.57)	−0.36 (−0.63)
$COF_{2,t}^M$	−0.20 (1.01)	−0.19 (−0.45)	−0.84 (−1.15)
$COF_{2,t}^L$	0.46 (1.63)	0.52 (1.14)	**1.40** (1.77)
$COF_{3,t}^S$	−0.21 (−0.68)	−0.43 (−0.85)	−1.14 (−1.31)
$COF_{3,t}^M$	**0.79*** (2.29)	**1.29*** (2.20)	**1.90*** (1.97)
$COF_{3,t}^L$	−0.02 (−0.10)	−0.13 (−0.31)	−0.12 (−0.14)
$COF_{4,t}^S$	0.21 (0.90)	0.33 (0.86)	0.76 (1.17)
$COF_{4,t}^M$	0.42 (1.51)	0.58 (1.20)	0.63 (0.76)
$COF_{4,t}^L$	0.09 (0.28)	0.21 (0.40)	0.14 (0.15)
$COF_{5,t}^S$	0.09 (0.22)	−0.27 (−0.38)	−1.25 (−1.03)
$COF_{5,t}^M$	0.02 (0.05)	0.37 (0.47)	0.48 (0.33)
$COF_{5,t}^L$	0.13 (0.35)	0.58 (0.82)	1.32 (1.06)
$Adj.R^2$	0.0042	0.0053	0.0041
$\Delta Adj.R^2$	0.0036	0.0047	0.0031

Table 6

Response of bond excess returns to lagged interdealer order flows in the LOB and OTC-market

	Sep.99 - Jun.05			Jul.05 - Nov.12			Sep.99 - Nov. 12		
	exr^{3Y}_{t+1}	exr^{5Y}_{t+1}	exr^{10Y}_{t+1}	exr^{3Y}_{t+1}	exr^{5Y}_{t+1}	exr^{10Y}_{t+1}	exr^{3Y}_{t+1}	exr^{5Y}_{t+1}	exr^{10Y}_{t+1}
$OFB^S_{1,t}$	−0.03 (−0.06)	−0.63 (−0.73)	−1.52 (−1.09)	0.47 (0.99)	0.05 (0.06)	−0.84 (−0.52)	0.25 (0.86)	−0.10 (−0.16)	−1.00 (−0.84)
$OFB^M_{1,t}$	0.83 (1.47)	0.91 (0.97)	2.54 (1.51)	0.62 (1.58)	$\mathbf{2.12}^{*}$ (2.85)	$\mathbf{2.68}^{*}$ (2.12)	$\mathbf{0.73}^{*}$ (2.29)	$\mathbf{1.67}^{*}$ (2.87)	$\mathbf{2.62}^{*}$ (2.64)
$OFB^L_{1,t}$	−0.20 (−0.41)	0.22 (0.25)	1.22 (0.67)	0.61 (1.50)	0.05 (1.31)	$\mathbf{2.33}$ (1.75)	0.41 (1.25)	0.89 (1.64)	$\mathbf{2.01}$ (1.90)
$OFO^S_{1,t}$	0.13 (0.22)	0.11 (0.12)	−0.31 (−0.18)						
$OFO^M_{1,t}$	−0.52 (−0.73)	−0.09 (−0.08)	−1.65 (−0.71)						
$OFO^L_{1,t}$	−0.64 (−0.95)	−1.08 (−0.99)	−2.62 (−1.28)						
$OFB^S_{2,t}$	0.44 (0.63)	0.18 (0.17)	−0.00 (−0.00)	0.88 (1.01)	1.68 (1.13)	3.73 (1.60)	0.62 (1.15)	0.68 (0.79)	1.20 (0.78)
$OFB^M_{2,t}$	0.30 (0.48)	0.95 (0.91)	2.71 (1.27)	0.22 (0.32)	0.31 (0.33)	0.47 (0.26)	0.21 (0.48)	0.55 (0.79)	1.57 (1.16)
$OFB^L_{2,t}$	$\mathbf{1.52}^{*}$ (2.79)	$\mathbf{2.21}^{*}$ (2.26)	$\mathbf{5.17}^{*}$ (2.32)	0.67 (1.20)	$\mathbf{1.84}$ (1.96)	$\mathbf{3.77}$ (2.28)	$\mathbf{0.95}^{*}$ (2.31)	$\mathbf{2.09}^{*}$ (2.91)	$\mathbf{4.34}^{*}$ (3.16)
$OFO^S_{2,t}$	0.40 (0.36)	1.29 (0.78)	2.89 (1.05)						
$OFO^M_{2,t}$	$\mathbf{1.93}$ (1.88)	$\mathbf{2.91}$ (1.80)	2.57 (0.81)						
$OFO^L_{2,t}$	$-\mathbf{1.29}$ (−1.81)	−1.71 (1.49)	−2.35 (1.06)						
$OFB^S_{3,t}$	0.82 (1.37)	1.56 (1.62)	1.18 (0.70)	0.22 (0.21)	−0.06 (−0.39)	−2.74 (−1.09)	0.65 (1.29)	0.86 (1.04)	−0.74 (−0.05)
$OFB^M_{3,t}$	$\mathbf{1.48}^{*}$ (2.24)	$\mathbf{1.86}$ (1.89)	1.34 (0.74)	1.14 (1.16)	2.95 (1.49)	3.02 (1.09)	$\mathbf{1.43}^{*}$ (2.56)	$\mathbf{2.36}^{*}$ (2.36)	2.26 (1.46)
$OFB^L_{3,t}$	0.07 (0.13)	0.18 (0.21)	0.08 (0.04)	1.17 (1.52)	$\mathbf{2.37}$ (1.76)	$\mathbf{4.72}$ (1.81)	0.36 (0.87)	0.83 (1.18)	1.33 (0.88)
$OFO^S_{3,t}$	−0.14 (−0.19)	−0.77 (−0.63)	−2.55 (−1.10)						
$OFO^M_{3,t}$	0.73 (0.72)	0.11 (0.07)	0.36 (0.12)						
$OFO^L_{3,t}$	−0.36 (−0.56)	0.02 (0.02)	0.64 (0.30)						
$OFB^S_{4,t}$	$\mathbf{1.27}$ (1.74)	1.19 (0.98)	−0.52 (−0.20)	$\mathbf{1.19}$ (1.87)	0.82 (0.89)	0.43 (0.24)	$\mathbf{1.31}^{*}$ (2.83)	1.16 (1.59)	0.39 (0.25)
$OFB^M_{4,t}$	0.49 (0.69)	1.01 (0.85)	1.46 (0.68)	0.13 (0.24)	1.56 (1.55)	2.53 (1.52)	0.16 (0.38)	1.14 (1.53)	1.87 (1.50)
$OFB^L_{4,t}$	0.99 (0.61)	$\mathbf{1.67}$ (1.89)	$\mathbf{4.11}^{*}$ (2.43)	−0.26 (−0.53)	−0.25 (−0.25)	2.02 (1.17)	0.29 (0.81)	0.69 (1.06)	$\mathbf{3.12}^{*}$ (2.60)
$OFO^S_{4,t}$	−0.27 (−0.28)	−0.28 (−0.20)	1.58 (0.64)						
$OFO^M_{4,t}$	0.09 (0.10)	0.23 (0.17)	−1.17 (−0.47)						
$OFO^L_{4,t}$	0.68 (0.60)	2.27 (1.33)	3.54 (1.36)						
$OFB^S_{5,t}$	$\mathbf{0.74}$ (1.92)	$\mathbf{1.22}^{*}$ (2.01)	1.61 (1.26)	0.59 (0.66)	0.81 (0.54)	1.45 (0.60)	$\mathbf{0.66}^{*}$ (1.97)	$\mathbf{1.08}^{*}$ (2.02)	1.41 (1.27)
$OFB^M_{5,t}$	$\mathbf{1.00}$ (1.86)	$\mathbf{2.04}^{*}$ (2.05)	2.86 (1.33)	−0.58 (−0.68)	−1.15 (−0.81)	−2.14 (−0.78)	0.25 (0.51)	0.61 (0.73)	0.57 (0.34)
$OFB^L_{5,t}$	−0.98 (−0.84)	−1.97 (−1.03)	−4.32 (−1.57)	$\mathbf{1.45}$ (1.65)	1.91 (1.31)	3.68 (1.59)	0.04 (0.05)	−0.38 (−0.29)	−1.21 (−0.69)
$OFO^S_{5,t}$	0.17 (0.15)	0.32 (0.19)	−0.98 (−0.32)						
$OFO^M_{5,t}$	−0.41 (−0.34)	0.88 (0.48)	2.66 (0.86)						
$OFO^L_{5,t}$	−0.79 (−0.69)	−1.44 (−0.72)	−3.07 (−0.78)						
$Adj.R^2$	0.0214	0.0193	0.0119	0.0137	0.0232	0.0249	0.0181	0.0209	0.0191

Table 7
Response of daily bond excess returns to passive order flow

The table presents the results of the following model over the period 1999-2012,
$exr^{(N)}_{t+1} = \beta_0 + \sum_{k=1}^{3} \beta_2^k F_t^k + \sum_{i=1}^{5}(\beta_3^i POFB^S_{i,t} + \beta_4^i POFB^M_{i,t} + \beta_5^i POFB^L_{i,t}) + e_{t+1}$,
where $POFB^S_{d,t}$, $POFB^M_{d,t}$, and $POFB^L_{d,t}$ are the short-, medium-, and long-term passive order flow in the LOB of Dealer d. Passive order flow is measured using limit orders with positive sign (negative) if dealer inventory increases (decreases). The regressions include a constant and the lagged three first principal components of forward rates. $\Delta Adj.R^2$ show the additional predictive power by adding the order flow variables. Coefficients are in basis points (0.01 percentage points) and corrected for autocorrelation and heteroscedasticity by the Newey-West method. Coefficients in bold are significant at the 10% level or better and an asterisk indicates that the coefficient is significant at the 5% level or better. T-statisics are in parentheses.

	$exr^{(1Y)}_{t+1}$	$exr^{(2Y)}_{t+1}$	$exr^{(3Y)}_{t+1}$	$exr^{(5Y)}_{t+1}$	$exr^{(7Y)}_{t+1}$	$exr^{(10Y)}_{t+1}$
$POFB^S_{1,t}$	−0.08	−0.38	−0.58	**−1.09**	**−1.58**	−1.29
	(−0.70)	(−1.51)	(−1.43)	(−1.77)	(−1.93)	(−1.15)
$POFB^M_{1,t}$	0.10	0.41	0.61	0.51	0.34	0.66
	(0.54)	(0.98)	(0.91)	(0.45	(0.23)	(0.37)
$POFB^L_{1,t}$	−0.06	**−0.47**	**−1.71**	**−1.58***	**−2.35***	**−3.66***
	(−0.59)	(−1.82)	(−1.65)	(−2.16)	(−2.34)	(−2.75)
$POFB^S_{2,t}$	**−0.43***	**−0.93***	**−1.20***	−1.05	−0.37	−0.12
	(−3.16)	(−3.44)	(−2.42)	(−1.21)	(−0.31)	(−0.07)
$POFB^M_{2,t}$	**−0.29***	**−0.53***	**−0.89**	**−1.80***	**−1.76**	−2.22
	(−2.42)	(−2.04)	(−1.95)	(−2.30)	(−1.70)	(−1.54)
$POFB^L_{2,t}$	−0.13	**−0.42**	**−0.76**	**−1.38**	**−2.17***	**−3.04***
	(−1.13)	(−1.68)	(−1.78)	(−0.90)	(−2.13)	(−2.08)
$POFB^S_{3,t}$	−0.11	−0.14	−0.25	−0.11	−0.72	−0.44
	(−0.69)	(−0.44)	(−0.54)	(−0.15)	(−0.70)	(−0.31)
$POFB^M_{3,t}$	0.03	0.23	0.01	−0.39	−0.60	−0.44
	(0.13)	(0.48)	(0.01)	(−0.34)	(−0.42)	(−0.23)
$POFB^L_{3,t}$	0.02	0.31	0.25	0.16	−0.17	−0.55
	(0.18)	(1.03)	(0.51)	(0.19)	(−0.15)	(−0.33)
$POFB^S_{4,t}$	−0.14	−0.01	0.12	0.39	1.10	0.52
	(−1.01)	(−0.05)	(0.27)	(0.55)	(1.09)	(0.71)
$POFB^M_{4,t}$	−0.28	**−0.85***	**−1.33***	**−2.57***	**−2.84***	**−3.08**
	(−1.45)	(−2.14)	(−2.14)	(−2.55)	(−2.16)	(−1.71)
$POFB^L_{4,t}$	−0.03	−0.14	−0.58	−1.11	**−2.07**	**−2.81**
	(−0.23)	(−0.44)	(−1.12)	(−1.29)	(−1.76)	(−1.76)
$POFB^S_{5,t}$	−0.24	−0.02	0.02	0.68	0.88	2.54
	(−1.19)	(−0.05)	(0.04)	(0.80)	(0.76)	(1.49)
$POFB^M_{5,t}$	−0.10	−0.45	−0.53	−0.31	−0.63	−0.35
	(−0.62)	(−1.44)	(−1.00)	(−0.33)	(−0.49)	(−0.20)
$POFB^L_{5,t}$	0.13	0.05	0.23	0.24	−0.36	−0.48
	(0.80)	(0.14)	(0.39)	(0.24)	(−0.27)	(−0.27)
$Adj.R^2$	0.0355	0.0208	0.0154	0.0170	0.0173	0.0163
$\Delta Adj.R^2$	0.0140	0.0169	0.0146	0.0165	0.0165	0.0153

Table 8

Predictive power of order flow on news days

Predictive power of each dealer's total order flow on news days defined as days with announcements from MPC-meetings, inflation numbers and retail sales and the following day. (beta is multilplied by 100))

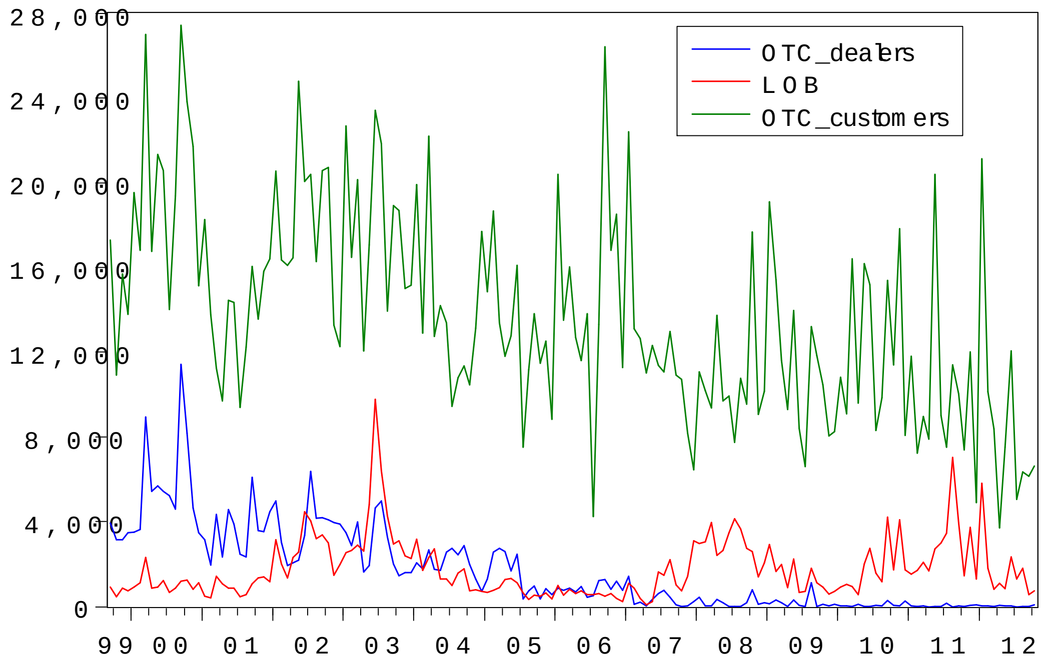
	Sep.99 - Jun.05			Jun.05 - Nov. 12		
	exr^{3y}_{t+1}	exr^{5y}_{t+1}	exr^{10y}_{t+1}	exr^{3y}_{t+1}	exr^{5y}_{t+1}	exr^{10y}_{t+1}
$OF^S_{1,t} * D^{news}_t$	0.001	−0.003	−0.005	−0.005	-0.016^{*}	-0.044^{**}
	(0.19)	(−0.29)	(−0.25)	(−0.98)	(−1.68)	(−2.42)
$OF^M_{1,t} * D^{news}_t$	0.002	−0.002	−0.004	$\mathbf{0.013}^{**}$	$\mathbf{0.029}^{***}$	$\mathbf{0.047}^{***}$
	(0.36)	(−0.28)	(−0.27)	(2.16)	(2.65)	(2.81)
$OF^L_{1,t} * D^{news}_t$	0.002	0.004	0.007	$\mathbf{0.016}^{**}$	$\mathbf{0.028}^{**}$	$\mathbf{0.054}^{***}$
	(0.26)	(0.34)	(0.28)	(2.21)	(2.32)	(2.66)
$OF^S_{2,t} * D^{news}_t$	0.000	0.003	0.013	0.007	0.026	0.057
	(0.09)	(0.29)	(0.81)	(0.42)	(0.84)	(1.26)
$OF^M_{2,t} * D^{news}_t$	0.012	0.021	0.034	0.005	0.008	0.012
	(1.58)	(1.59)	(1.06)	(0.37)	(0.43)	(0.37)
$OF^L_{2,t} * D^{news}_t$	−0.008	−0.005	−0.007	0.005	0.004	0.019
	(−0.86)	(−0.30)	(−0.26)	(0.54)	(0.23)	(0.73)
$OF^S_{3,t} * D^{news}_t$	−0.005	−0.011	−0.042	−0.008	−0.022	−0.057
	(−1.05)	(−1.25)	(−2.11)	(−0.62)	(−1.17)	(−1.89)
$OF^M_{3,t} * D^{news}_t$	−0.001	−0.008	−0.030	0.015	0.019	−0.005
	(−0.12)	(−0.65)	(−1.16)	(1.03)	(0.76)	(−0.15)
$OF^L_{3,t} * D^{news}_t$	−0.011	−0.015	−0.023	−0.001	0.015	$\mathbf{0.069}^{**}$
	(−1.87)	(−1.70)	(−1.12)	(−0.03)	(0.66)	(2.11)
$OF^S_{4,t} * D^{news}_t$	0.004	0.008	0.002	0.018	0.029	0.026
	(0.69)	(0.79)	(0.10)	(0.91)	(0.94)	(0.42)
$OF^M_{4,t} * D^{news}_t$	−0.006	−0.010	−0.030	−0.011	−0.006	−0.014
	(−0.76)	(−0.79)	(−1.37)	(−1.22)	(−0.37)	(−0.48)
$OF^L_{4,t} * D^{news}_t$	0.009	$\mathbf{0.020}^{*}$	$\mathbf{0.045}^{*}$	−0.005	−0.008	0.006
	(1.24)	(1.76)	(1.96)	(−0.53)	(−1.42)	(0.20)
$OF^S_{5,t} * D^{news}_t$	0.003	0.064	0.003	0.031	$\mathbf{0.057}^{*}$	0.077
	(0.41)	(1.01)	(0.13)	(1.63)	(1.86)	(1.65)
$OF^M_{5,t} * D^{news}_t$	0.007	$\mathbf{0.018}^{*}$	0.025	0.017	0.021	0.045
	(1.23)	(1.79)	(1.24)	(1.45)	(1.19)	(1.50)
$OF^L_{5,t} * D^{news}_t$	0.008	0.011	0.007	$\mathbf{0.023}^{*}$	0.036	0.074
	(0.94)	(0.80)	(0.28)	(1.69)	(1.42)	(1.59)
$Adj.R^2$	−0.002	−0.000	0.000	0.008	0.012	0.017

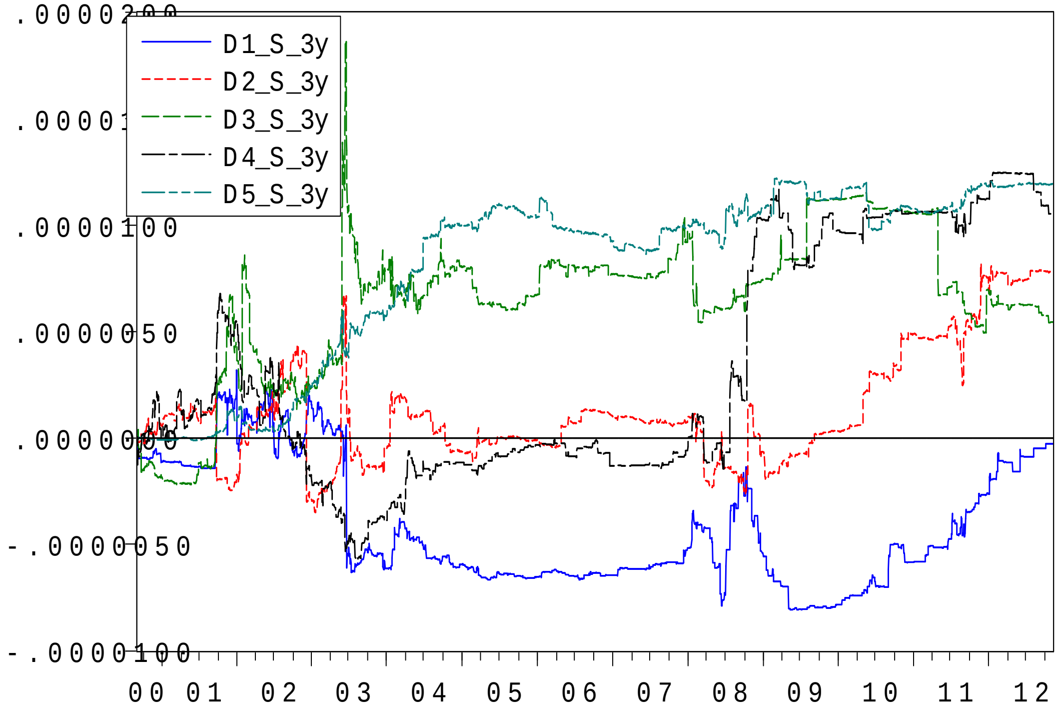
Table 9
Summary for each dealer and each maturity group

The table shows which types of order flows that have predictive power for each dealer and whether they predict better on news days.

	LOB OF			OTC OF			Passive	Customer OF			Info
	exr3	exr5	exr10	exr3	exr5	exr10	LOB OF	exr3	exr5	exr10	
Dealer 1											
Short OF	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	-
Medium OF	**Yes**	**Yes**	**Yes**	*No*	*No*	*No*	*No*	**Yes**	**Yes**	**Yes**	News
Long OF	*No*	*No*	*Yes*	*No*	*No*	*No*	**Yes**	*No*	**Yes**	**Yes**	News
Dealer 2											
Short OF	*No*	*No*	*No*	*No*	*No*	*No*	**Yes**	*No*	*No*	*No*	
Medium OF	*No*	*No*	*No*	*Yes*	*Yes*	*No*	**Yes**	*No*	*No*	*No*	-
Long OF	**Yes**	**Yes**	**Yes**	*No*	*No*	*No*	**Yes**	*No*	*No*	**Yes**	-
Dealer 3											
Short OF	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	-
Medium OF	**Yes**	**Yes**	*No*	*No*	*No*	*No*	*No*	**Yes**	**Yes**	**Yes**	-
Long OF	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	News
Dealer 4											
Short OF	**Yes**	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	-
Medium OF	*No*	*No*	*No*	*No*	*No*	*No*	**Yes**	*No*	*No*	*No*	-
Long OF	*No*	*No*	**Yes**	*No*	*No*	*No*	**Yes**	*No*	*No*	*No*	News
Dealer 5											
Short OF	**Yes**	**Yes**	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	News
Medium OF	*No*	**Yes**	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	News
Long OF	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	*No*	-

Figure 1: Trading volume in the electronic limit order book (LOB, red curve)) and in the over–the-counter market (OTC, blue and green curves) in Norwegian government bonds. The blue curve represents interdealer trading in the OTC-market and the green curve represents customer trades. Monthly trading volume from September 1999 to November 2012. Million NOK.





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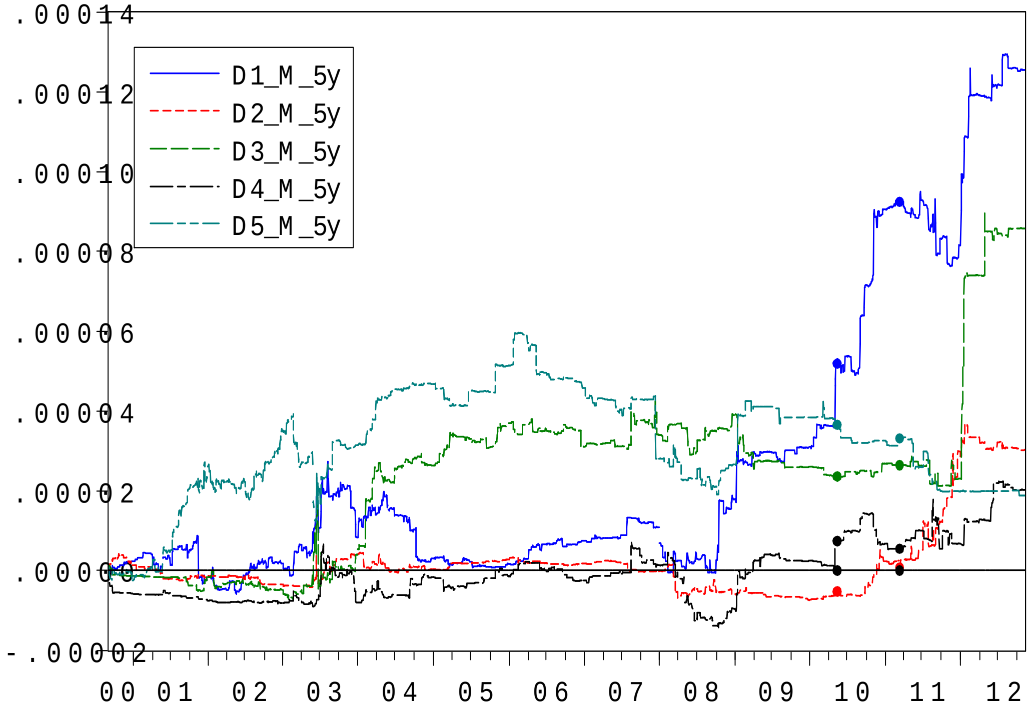

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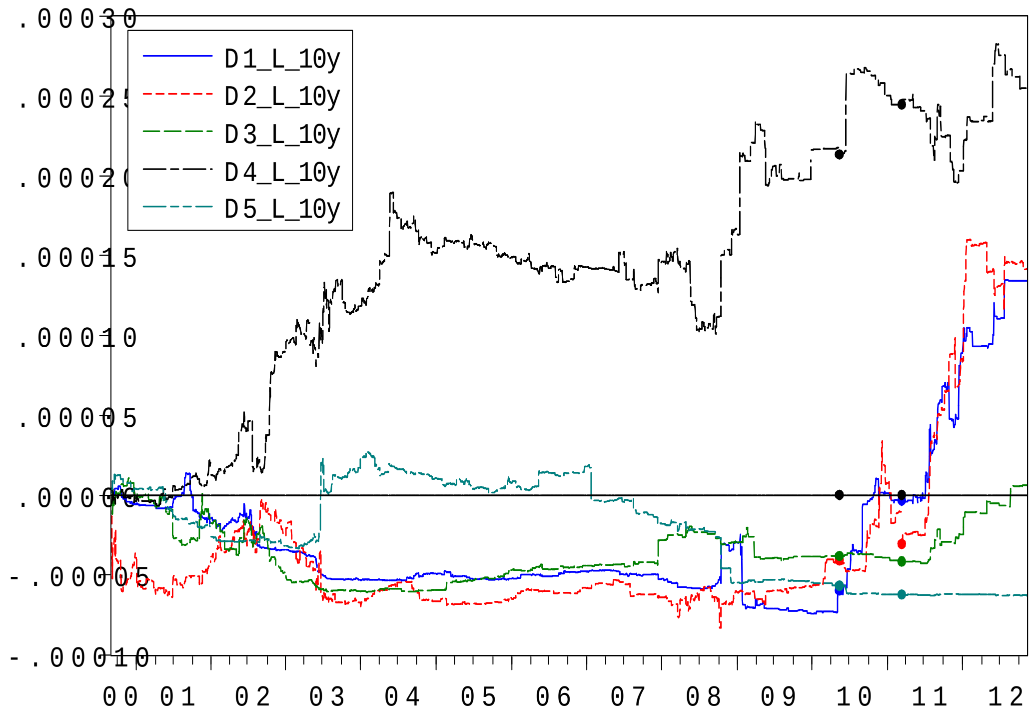

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D3_L_10y
D4_L_10y
D5_L_10y

Figure 2: Yield to maturity for 3 year (blue), 5 year (green), and 10 year (black) Norwegian government bonds, and the monetary policy rate (red) which is the banks' deposit rate in the central bank. September 1999 to November 2012

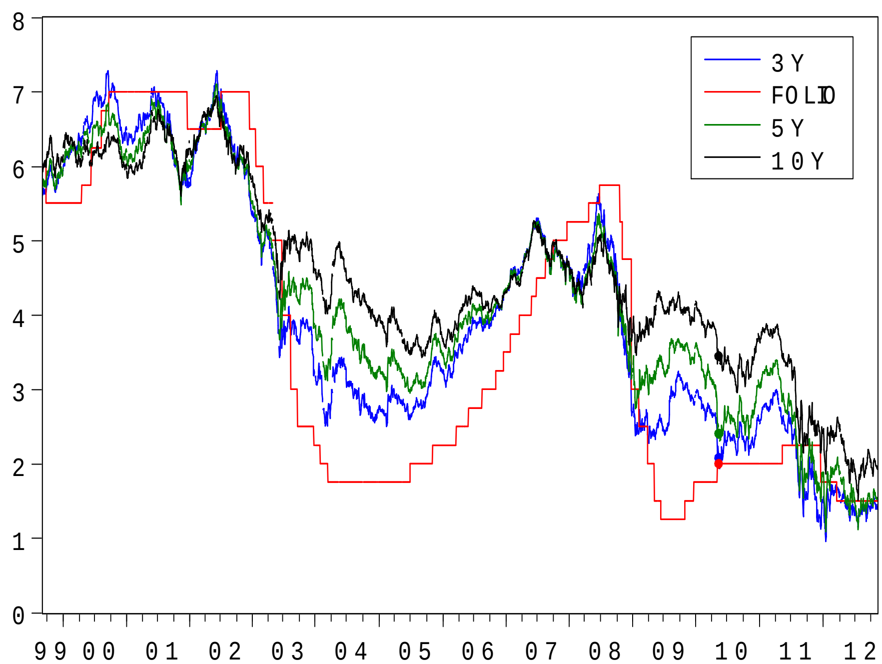

Figure 3: Out-of-sample forecasts of daily excess return on 5 year government bonds using Dealer 1 interdealer orderflow in the LOB (solid line) and in the OTC-market (dotted line) in medium term bonds. The passive LOB medium term order flow (dashed line) is based on Dealer 1's limit order trades. An increase in the passive order flow implies an increase in Dealer 1's inventory of medium term bonds. The curves illustrate the cumulative squared prediction errors of the naive model minus the squared prediction errors of the interdealer order flow model, over the estimation period. The difference in prediction errors is measured along the vertical axis and the time period is measured along the horizontal axis. In periods when a curve increases, the order flow model predicts better. In periods when it decreases the naive model gives the best predictions. Recursive estimation for the period September 2000 to November 2012.

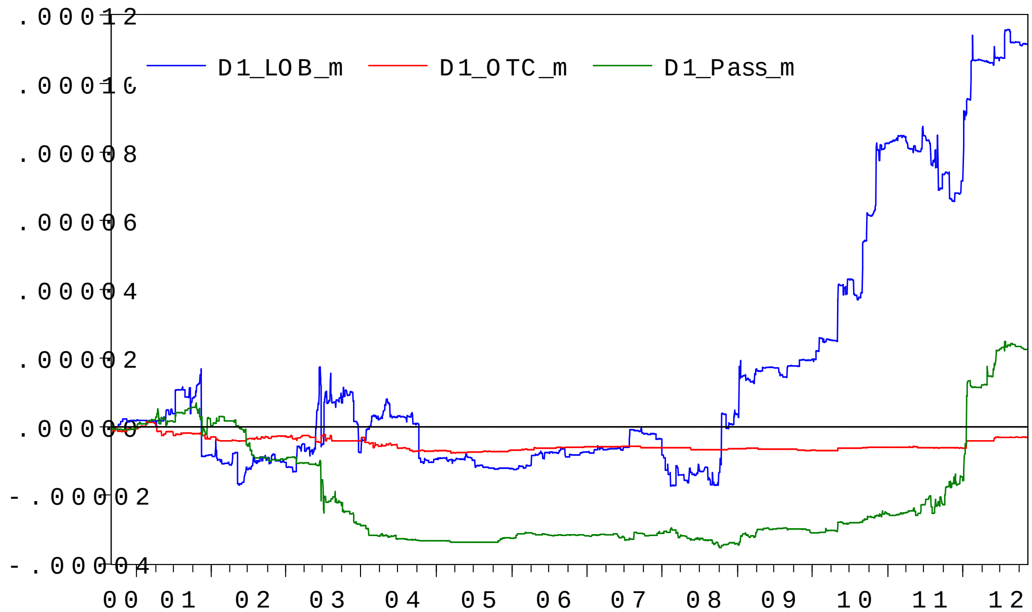

Figure 4: Out-of-sample forecasts of daily excess return on 10 year government bonds using Dealer 2 interdealer orderflow in the LOB (solid line) and in the OTC-market (dotted line) in long term bonds. The passive LOB long term order flow (dashed line) is based on Dealer 2's limit order trades. An increase in the passive order flow implies an increase in Dealer 2's inventory of long term bonds. The curves illustrate the cumulative squared prediction errors of the naive model minus the squared prediction errors of the interdealer order flow model, over the estimation period. The difference in prediction errors is measured along the vertical axis and the time period is measured along the horizontal axis. In periods when a curve increases, the order flow model predicts better. In periods when it decreases the naive model gives the best predictions. Recursive estimation for the period September 2000 to November 2012.

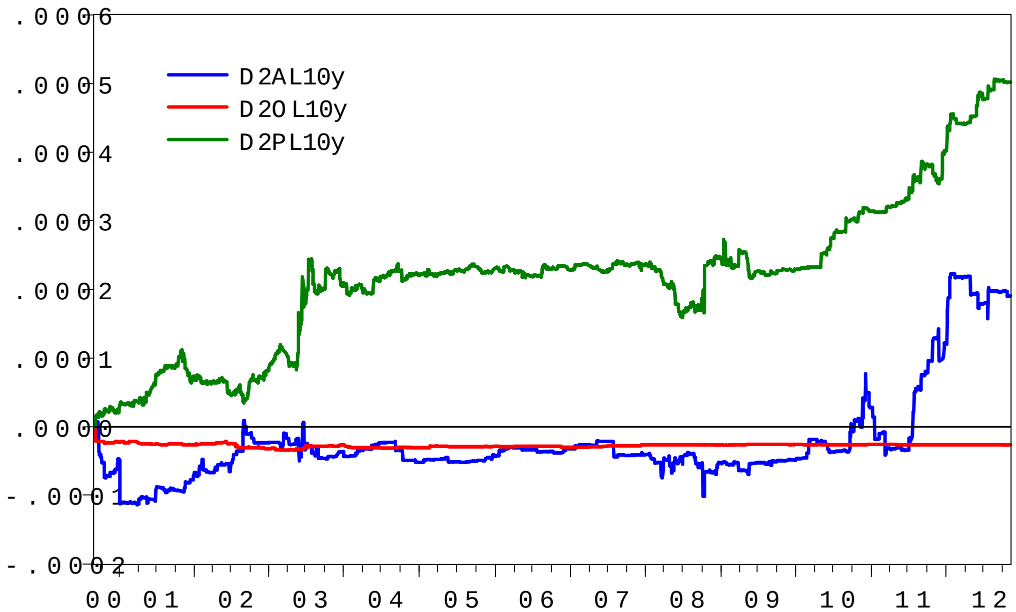

Figure 5: Out-of-sample forecasts of daily excess return on 5 year government bonds using Dealer 3 interdealer orderflow in the LOB (solid line) and in the OTC-market (dotted line) in medium term bonds. The passive LOB medium term order flow (dashed line) is based on Dealer 3's limit order trades. An increase in the passive order flow implies an increase in Dealer 3's inventory of medium term bonds. The curves illustrate the cumulative squared prediction errors of the naive model minus the squared prediction errors of the interdealer order flow model, over the estimation period. The difference in prediction errors is measured along the vertical axis and the time period is measured along the horizontal axis. In periods when a curve increases, the order flow model predicts better. In periods when it decreases the naive model gives the best predictions. Recursive estimation for the period September 2000 to November 2012.

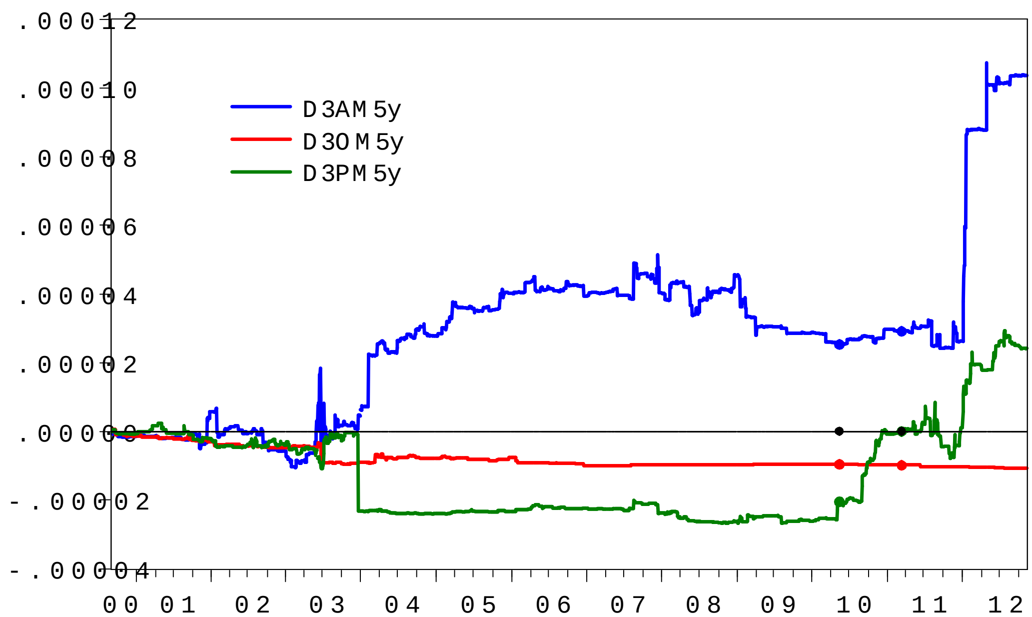

Figure 6: Out-of-sample forecasts of daily excess return on 10 year government bonds using Dealer 4 interdealer orderflow in the LOB (solid line) and in the OTC-market (dotted line) in long term bonds. The passive LOB long term order flow (dashed line) is based on Dealer 4's limit order trades. An increase in the passive order flow implies an increase in Dealer 4's inventory of long term bonds. The curves illustrate the cumulative squared prediction errors of the naive model minus the squared prediction errors of the interdealer order flow model, over the estimation period. The difference in prediction errors is measured along the vertical axis and the time period is measured along the horizontal axis. In periods when a curve increases, the order flow model predicts better. In periods when it decreases the naive model gives the best predictions. Recursive estimation for the period September 2000 to November 2012.

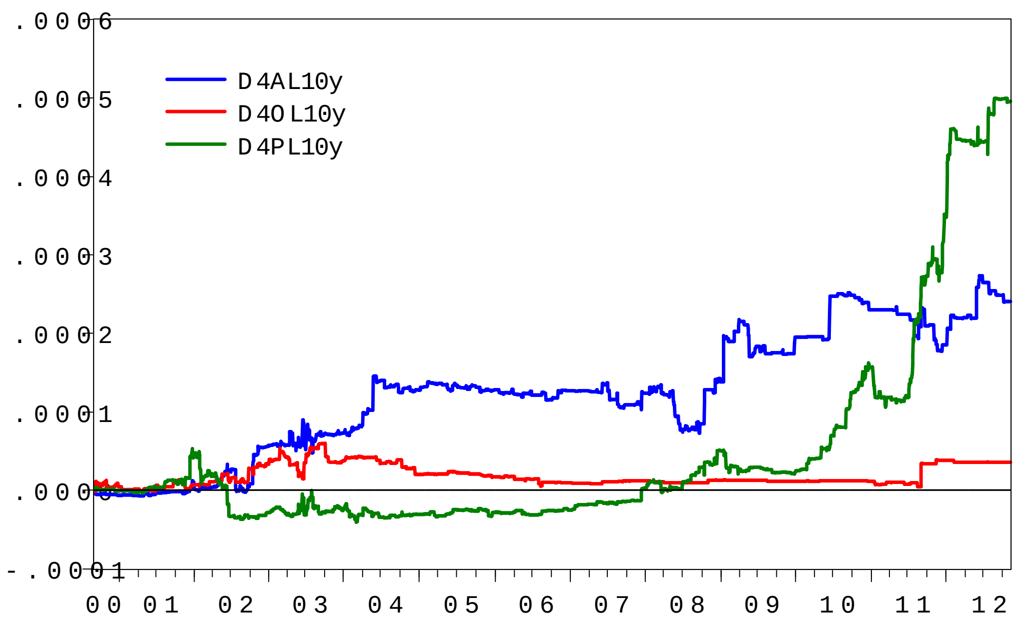

Figure 7: Out-of-sample forecasts of daily excess return on 5 year government bonds using Dealer 5 interdealer orderflow in the LOB (solid line) and in the OTC-market (dotted line) in medium term bonds. The passive LOB medium term order flow (dashed line) is based on Dealer 5's limit order trades. An increase in the passive order flow implies an increase in Dealer 5's inventory of medium term bonds. The curves illustrate the cumulative squared prediction errors of the naive model minus the squared prediction errors of the interdealer order flow model, over the estimation period. The difference in prediction errors is measured along the vertical axis and the time period is measured along the horizontal axis. In periods when a curve increases, the order flow model predicts better. In periods when it decreases the naive model gives the best predictions. Recursive estimation for the period September 2000 to November 2012.