Forecasting short term yield changes using order flow: Is dealer skill a source of predictability?

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Abstract

Bond market order flow contains information about future yield changes that is not incorporated into the current yield curve. This paper documents that term structure models that include interdealer order flow outperform traditional term structure models and the random walk both in-sample and out-of-sample. A unique data set, including customer trades and interdealer trades of individual dealers, enables the paper to explore the sources of predictability in interdealer order flow. The results suggest that dealer skill in acquiring and interpreting information can be one source. Predictability appears to be related to dealer activity rather than to dealer size and customer base.

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1 Introduction

The classical expectations hypothesis implies that forward rates can predict future interest rates, but empirical studies suggest otherwise. Fama and Bliss (1987) and Campbell and Shiller (1991) find that forward rates predict bond excess returns, a measure of the risk premium which is assumed constant in the expectations hypothesis, rather than future short rates. This is confirmed by Cochrane and Piazzesi (2005) who conclude that bond yields contain time-varying risk premia and that these can be predicted by a single forward rate factor. Recent studies suggest that information beyond that contained in the yield curve can predict bond yields. Ludvigson and Ng (2009) find that macroeconomic factors have important forecasting power for bonds above the predictive power of forward rates. Andersen and Benzoni (2010) conclude that bond market volatility cannot be predicted by information in the current yield curve and suggest that the term structure modeling framework should be extended to include macroeconomic and monetary policy variables. The purpose of this paper is to explore whether bond market order flow, which can reflect macroeconomic information, has forecasting power for yield changes and if so, to identify the sources of predictability.

Order flow is defined as the number of buyer-initiated trades minus the number of seller-initiated trades during a day and can reflect private information about asset prices held by traders.[1] Private information can include interpretations of macroeconomic indicators as well as dispersed private information related to market liquidity, hedging activity and the perception of risk among market participants. In other words, order flow can convey information of fundamental and non-fundamental character held by agents trading in the market. Several market microstructure studies have documented a relationship between order flow and asset prices. Evans and Lyons (2002), Hasbrouck (1991) and Brandt and Kavajecz (2004) find that order flow contains information about contemporaneous changes in exchange rates, stock prices and bond yields, respectively. Evans and Lyons (2005) show that foreign exchange market order flow also contains information about future exchange rates. They document that exchange rate forecasts based on order flow outperform forecasts based on macroeconomic variables and the random walk.

[1]Positive order flow indicates a net buying pressure and negative order flow indicates a net selling pressure during a day.

This paper makes three contributions. First, it introduces lagged bond market order flow as a new variable in a term structure model. Bond market order flow is separated into three maturity groups according to the maturity of the bonds traded. Second, it employs both aggregate and individual dealer order flow in the predictive regressions. Third, it includes order flow from both tiers in the sovereign bond market; the customer market and the interdealer market. The paper employs a unique data set from Norway including all bond trades with dealer identities from September 1999 to September 2005. This facilitates the separation of interdealer trades from customer trades both at the aggregate level and the individual dealer level. The paper can therefore address questions that cannot be addressed using other data sets such as GovPX, which contains US Treasury interdealer trades, but does not include customer trades or dealer identities.[2] Other frequently used data sets contain customer trades from a specific financial institution or from the one tier bond futures market. These data sets are unable to capture dealer heterogeneity or the dynamics between dealers and their customers.

One interesting topic, so far unexplored empirically due to a lack of data, is the sources of predictive power in aggregate interdealer order flow. Two sources of predictability in order flow are considered; informed customer trades and dealer skill. Dealer skill is defined as dealer ability to acquire and process relevant information beyond the information contained in the dealer's customer trades. This could be interpretations of public information, information from other market participants or information obtained by observing and engaging in trades in the interdealer market. Thus, if the interdealer order flow of an individual dealer has predictive power it could be either because she has the ability to identify her informed customer trades or because she has the skill to acquire and interpret other relevant public and private information. If the source of predictability is informed customer trades, both the customer order flow and the interdealer order flow of a dealer are expected to have predictive power. If the source of predictability is dealer skill, only the interdealer order flow of a dealer is expected to have predictive power.

The predictive power of individual interdealer order flow can be related to the role

[2] According to Fleming and Remolona (1997) GovPX data includes best bid and offers, trade prices and trade sizes and the aggregate volume of trading for all Treasury securities from five of the six major primary dealers/interdealer brokers accounting for roughly two thirds of the interdealer market. Brandt and Kavajecz (2004) find that this volume represents roughly 45 percent of the trading volume in the secondary market for Treasury securities.

of dealers in the price formation process. Are dealers passive intermediaries of customer trades or are they actively collecting and trading on information? If dealers are passive intermediaries their interdealer order flow is likely to be uninformed. Their customer order flow can have predictive power if their customers on average are informed. If dealers are active information collectors, by identifying informed customers or by acquiring information from other sources, their interdealer order flow is likely to have predictive power. While traditional market microstructure models, for example Glosten and Milgrom (1985) and Kyle (1985), leave no room for active dealers, there is some empirical evidence that dealers have an active role in the price formation process. Manaster and Mann (1996) and Anand and Subrahmanyam (2008) find that dealers are not mere intermediaries of customer trades, but actively seek and aggregate information in the markets for commodity futures and stocks, respectively. Peiers (1997) and Sapp (2002) document that some dealers in the foreign exchange market consistently incorporate new information into their quotes before others. Unlike previous empirical studies this paper can investigate dealer heterogeneity and the sources of predictability in interdealer order flow directly.

There are two sets of results in this study, the first is based on aggregate order flow and the second is based on individual dealer order flow. The first set of results documents that models including bond market order flow make better predictions than traditional term structure models. Aggregate interdealer order flow has predictive power over and above that of forward rates indicating that it contains information about future bond prices that is not fully incorporated into the current yield curve. Term structure models including order flow also outperform the random walk model. Lagged interdealer order flow forecasts changes in bond yields of maturities from one to ten years at both daily and monthly horizons. For example, a one standard deviation increase in daily medium term order flow, defined as the order flow based on bonds with a remaining time to maturity between 4 and 7 years, predicts a fall in the 3-year yield of 0.44 basis points the next day. An increase in monthly medium term order flow of one standard deviation, predicts a 5.86 basis point decrease in the 3-year yield in the following month. The fact that both daily and monthly interdealer order flow have predictive power indicates that order flow contains different types of information and that it may take a month or more for some types of information to become fully incorporated into bond prices.

The second set of results suggests that the sources of predictive power in interdealer order flow are both informed customer trades and dealer skill in acquiring and interpreting relevant information. The results document that the interdealer order flow of some, but not all, of the dealers have predictive power for future yield changes. At the daily horizon the interdealer order flow of two of the four large dealers have predictive power along the whole yield curve. While the customer order flow of one of these dealers also has predictive power, the customer order flow of the other does not. This suggests that the main source of predictability for the first dealer is customer trades while it is dealer skill for the second dealer. At the monthly horizon the interdealer order flows of the same two dealers, and a third large dealer, have predictive power. However, the customer order flows of these three dealers have no forecasting ability, indicating that customer trades are not an important source of predictability at the monthly horizon.

The results further indicate that the forecasting ability of individual interdealer order flow is related to whether dealers are passive intermediaries or active market participants rather than to dealer size and customer base. The paper employs two measures of dealer activity. The first is the value of a dealer's active (initiated) interdealer trades over the value of her customer trades. The second is the number of active interdealer trades relative to the number of passive (initiated by another dealer) interdealer trades. Active dealers are characterized by a high score on both measures while passive dealers are characterized by a low share. When comparing the scores of the four large dealers in this study, the three dealers with predictive interdealer order have relatively high scores while the last dealer has a much lower score on both measures. This dealer has the largest customer base but her interdealer order flow has no forecasting ability on either the daily or monthly horizon indicating that this dealer is a passive, uninformed intermediary.

Bond yields can be decomposed into expected average future short interest rates and a risk premium. To better understand the type of information contained in order flow, the predictive power of order flow on both yield changes and bond excess returns is explored. To preserve space the results for bond excess returns are not included in the paper, but are available upon request. The results document that order flow has roughly the same explanatory power for yield changes and excess returns, while forward rates are better predictors of excess returns than of yield changes. These findings suggest that order flow predicts risk premia, but risk premia beyond, and perhaps different from, those predicted by forward rates.

The rest of the paper is organized as follows. Section 2 gives an overview of the related literature. Section 3 describes the data set and trading conventions in the Norwegian government bond market. Section 4 presents the theoretical background and econometric framework. Sections 5 and 6 report the results based on aggregate interdealer order flow in-sample and out-of-sample, respectively. Section 7 presents the in-sample and out-of-sample results based on individual dealer order flow. Finally, section 8 concludes.

2 Related literature

This paper is related to several segments of the finance literature; the market microstructure literature, the term structure literature, and the literature on asset return predictability. The market microstructure literature has documented that order flow contains information about asset prices. Studies on bond markets include Brandt and Kavajecz (2004) who find that up to 26 percent of contemporaneous daily yield changes in the U.S. Treasury market can be accounted for by interdealer order flow. Pasquariello and Vega (2007) show that unanticipated order flow in US treasuries has a significant and permanent impact on daily bond yield changes on news days as well as on no-news days.[3] Valseth (2011) finds similar results from the Norwegian government bond market. This paper has a different approach by focusing on the role of order flow as a predictor of future yield changes.

The predictive power of currency market order flow is documented by Evans and Lyons (2005). They find that models including order flow in foreign exchange markets have significant out-of-sample forecasting power for exchange rates and outperform both macroeconomic models and the random walk. Evans and Lyons (2008) document that order flow can forecast both the exchange rate and its underlying macroeconomic determinants. The present study is related to Evans and Lyons (2005, 2008), but differs in several ways besides investigating a different asset market. First, it employs both interdealer order

[3]They define unanticipated order flow as the order flow over thirty minute intervals that are not explained by lagged thirty minute order flow or thirty minute quote revision. They use 19 lags which equals a trading day. Unanticipated order flow is calculated by adding up the 19 error terms within each day.

flow and customer order flow. Second, it uses individual dealer order flow to investigate possible sources of predictability. Third, it attempts to reveal whether the information contained in order flow is related to bond risk premia by studying the predictive power of order flow on both yield changes and excess returns. Fourth, while Evans and Lyons (2005) use overlapping daily data at the monthly horizon but do not test for a possible bias due to the persistence of overlapping observations, this paper addresses the potential problem by employing non-overlapping data at the monthly forecasting horizon.

Asymmetrically informed dealers are discussed by Peiers (1997) and Sapp (2002). They investigate the price setting behavior of dealers in the foreign exchange market. Both find that some dealers are price leaders, which means that they incorporate new information into their prices before others, after the central bank has intervened in the foreign exchange market. While Peiers (1997) and Sapp (2002) investigate the role of dealer pricing behavior in the transmission of information between dealers, this paper takes a different approach by investigating the role of different dealers' trading behavior in the price formation process.

Green (2004) finds that the informational role of trading increases after macroeconomic announcements, suggesting that the release of public information increases the information asymmetry in the market. Menkveld et al. (2011) conclude that intermediaries in the one-tier Treasury futures market rely on their customer order flow after macro announcements to discover the full price impact. While Peiers (1997) and Sapp (2002) use individual dealer quotes, Green (2004) uses aggregate interdealer order flow and Menkveld et al. (2011) use dealer trades made on behalf of customers, this paper contributes by using individual dealer order flow in both tiers of the bond market to better understand the origins of predictability in interdealer order flow.

This paper is also related to the vast literature on the term structure of interest rates and the expectations hypothesis. Fama and Bliss (1987) and Campbell and Shiller (1991) find that forward rates and yield spreads have little predictive power for future interest rates. Instead they find that forward rates can predict bond excess returns, a measure of the risk premium, and conclude that the bond risk premium varies over time and is predictable. Cochrane and Piazzesi (2005) strengthen the evidence against the expectations hypothesis by showing that a linear combination of all forward rates can predict bond risk premia at one year horizons. Kessler and Scherer (2009) apply the Cochrane and Piazzesi

(2005) model to international bond markets, and confirm that the model applies to these markets also. This study builds on the above papers but adds order flow as a predictor variable and has shorter forecasting horizons.

Recent studies highlight the importance of using information beyond that contained in the yield curve. Ludvigson and Ng (2008) find that macroeconomic fundamentals can forecast variation in bond excess returns. They perform a principal components analysis of more than 100 macroeconomic indicators and find that lagged common factors have significant forecasting power also out-of-sample. Andersen and Benzoni (2010) find that bond market volatility cannot be predicted with information from the current yield curve and indicate that macroeconomic and monetary policy variables influence the fluctuations in interest rates. Ilmanen (1995) shows that financial market variables can forecast excess government bond returns in six countries. Cooper and Priestley (2008) document that the output gap has predictive power for both stock excess returns and bond excess returns. The present study differs from previous studies by using order flow, which can contain both fundamental and non-fundamental information, as a predictor variable. Some of the information reflected in order flow can be related to the macroeconomic outlook, thus supporting the findings of the above mentioned studies.

Finally, this paper is related to Goyal and Welch (2008) who reexamine the performance of variables that have been suggested to be good predictors of the equity premium. 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. They illustrate the performance of a predictor variable over time by calculating a metric comparing the cumulative squared prediction errors of the model including the predictive variable to that of the random walk. This paper follows the recommendation by Goyal and Welch (2008) and modifies their method to examine the out-of-sample predictive power of predictors of the bond risk premium.

3 Data and trading environment

3.1 The secondary market for Norwegian government bonds

The secondary market for Norwegian government bonds is organized similarly to major government bond markets. It is a two-tier market consisting of an interdealer market and a customer market. Dealers in government bonds have to be members of the Oslo Stock Exchange (OSE) and authorized for bond trading. Membership may be granted to Norwegian and foreign investment firms authorized to provide investment services in Norway or in their country of origin. A majority of the dealers are primary dealers appointed by the Central Bank. Typically, primary dealers are banks and brokerage firms. The number of primary dealers has varied between 5 and 8 during the sample period. In order to secure a liquid and well functioning market, primary dealers are obliged to provide firm bid and ask prices within a maximum spread for all benchmark bonds during market opening hours from 9 a.m. to 4 p.m. Other participants in the secondary market are bond dealers that are not primary dealers and non-dealers referred to as customers. The interdealer market is the market between dealers. All dealers are connected to the OSE electronic trading system. Interdealer trades can thus be electronic trades or "over-the-counter" trades.[4] The customer market is the market between bond dealers and their customers. Customers in general do not have access to the electronic trading system and must execute their bond trades through dealers. Customers may be institutional investors, commercial firms and individuals.

The data set employed in this paper is unique in that it contains data making it possible to distinguish trades in the two markets for each dealer. Customer trades and interdealer trades can be separated by applying the identity of the buying and the selling dealer. Transactions with different buying and selling dealers are defined as interdealer trades, and transactions with the same buying and selling dealer are defined as customer trades. The interdealer market constitutes about 35 percent of the total market measured in number of trades, and about 25 percent measured in value (NOK). Interdealer trades in this study are on average around 22 million NOK, and customer trades are on average

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

around 36 million NOK. All trades have to be registered in the OSE electronic trading system within 5 minutes after they are agreed upon. The trades are normally visible to other traders in the electronic order book shortly after the trade and at the latest by 4 p.m.

3.2 Data

The analysis in this paper is based on a data set that covers all trades in the Norwegian government bond market from September 6, 1999 to September 30, 2005. The number of bonds in the market varies between four and six benchmark bonds with a remaining time to maturity between 1 and 11 years. The bonds are issued, and subsequently expanded, in the primary market according to a pre-announced auction calendar. There are typically six to eight bond auctions during a year and they are conducted as uniform price (Dutch) auctions. Every other year a new 11 year bond is issued. The new bond will reach its full size several years after it was first issued.

The data set includes all transactions in the benchmark bonds and the best bid and ask prices submitted by the dealers. Each transaction includes date, time, price, amount, and the identity of the buying and the selling dealer. A total of 66,650 transactions, both electronic trades and over-the-counter trades, are included in the construction of daily and monthly order flow data.

Order flow, the key explanatory variable in this study, is constructed by signing the bond transactions according to the method of Lee and Ready (1991).[5] The signed trades are then aggregated into daily order flow. Daily order flow is defined as the number of buyer-initiated trades minus the number of seller-initiated trades during a day. Order flow is divided into three maturity segments according to the remaining time to maturity of the bonds being traded. Short term order flow includes bonds with a remaining time to maturity from 1 to 4 years, medium term order flow includes bonds with a remaining time to maturity greater than 4 years up to 7 years and long term order flow includes trades in

[5] Since the dealer identities do not indicate which dealer initiated the trade, the method of Lee and Ready (1991) is used to sign the trades. Trades that are executed at a price less than the mid price are classified as seller-initiated, and trades that are executed at a price higher than the mid price are classified 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.

bonds with a remaining time to maturity greater than 7 years. Since long bonds gradually increase in size some bonds included in long term order flow can be somewhat less liquid than the bonds included in the other two categories.

This study employs zero coupon yields and forward rates for Norwegian government bonds.[6] These yields are calculated from end-of-day prices of government bonds and government bills using the Nelson-Siegel algorithm. The zero-coupon bond yields are used to calculate daily and monthly yield changes and excess returns of 1, 2, 3, 4, 5, and 10 year bonds. One month forward rates 1, 2, 3, 4, 5 and 10 years ahead, are used to calculate forward spreads and principal components of forward rates.

3.3 Descriptive statistics

Table 1 Panel A and Panel B show the decomposition of forward rates into principal components. Panel A presents the six factors extracted from the one month forward rates maturing in 1, 2, 3, 4, 5 and 10 years. The panel shows that the first factor explains 92.8 percent of total variance, whereas the second and third factors explain 6.6 and 0.5 percent respectively. This implies that the first three components explain 99.9 percent of the variation in forward rates. Instead of using forward rates in the predictive regressions, the three first principal components are used. Panel B shows the loadings of the three factors on the forward rates. The first factor loads about equally on all forward rates. This makes it comparable to the "level" factor described by Litterman and Scheinkman (1991). The second and third principal components of forward rates correspond to the "slope" and "curvature" factors.[7]

This study uses both daily data and monthly data. To preserve space only descriptive statistics based on daily data are presented. Table 2 Panel A shows that daily yield changes are slightly negative on average. The decline in interest rates is related to the monetary policy during the sample period. The Norwegian Central Bank cut the key interest rate from 7 percent in December 2002 to 1.75 percent in 2004 in response to an inflation level below target. The one month rate is therefore the most volatile rate with a standard error

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

[7] 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.

of 7 percent. Yields on 2, 3, 4 and 5 year bonds are more volatile than 1 and 10 year yields. The persistence, measured by the AR(1) coefficient, appears to be relatively low for daily yield changes. It should be noted, however, that it is considerably higher at the very short end of the yield curve than at the long end.

The panel further shows that interdealer order flow for all three maturity segments on average have a net selling pressure over the sample period. However, there are distinct differences. Medium term order flow has the lowest average selling pressure, the lowest standard error and by far the lowest persistence. Long term order flow appears to be the most volatile variable, whereas the short term order flow is the most persistent variable. Finally, Panel A shows that the principal components of forward rates and the Fama-Bliss forward spreads are very persistent on a daily basis. The AR(1) coefficients are in excess of 99 percent for all series, except for the third principal component. The first principal component of forward rates is clearly more volatile than the two other principal components. The average value and the standard error of the forward spreads increase with the maturity of the forward rates, which is expected as the forward spread is defined as the forward rate minus a short term interest rate. This paper uses the one month rate as the short term interest rate.

Table 2 Panel B presents the correlations between the predictive variables. It appears that short, medium and long term interdealer order flows are positively correlated with a correlation around 20 percent at the daily horizon. These relatively low levels of correlation imply that multicollinearity is not a problem at the daily horizon. The correlation between short and medium term interdealer order flow is higher at the monthly than at the daily frequency. However, multicollinearity does not appear to be a problem at the monthly horizon as the order flow variables are statistically significant in the in-sample predictions.

4 Theoretical background and econometric framework

4.1 Market microstructure

While traditional term structure models assume that asset prices instantaneously reflect all new information, market microstructure theory focuses on the process of price formation over time. According to O'Hara (2003) the price formation process, in which asset prices adjust to full information prices, do not occur instantaneously, but evolves in markets over time. Lyons (2001) describes how new information is embedded into asset prices through a direct channel and an indirect channel. Through the direct channel public information is embedded into prices instantaneously. Through the indirect channel, also referred to as price discovery, information is gradually incorporated into prices through trading activity. Order flow contains private information which is reflected in asset prices over time. Dealers observe the order flow, infer private information, update their expectations and set prices accordingly. Private information may include heterogeneous interpretations of public information as well as dispersed information related to liquidity, hedging demands and investor risk preferences.

For bond markets, the main implication of the differences between the traditional asset pricing literature and the market microstructure literature is how to interpret the yield curve. According to the traditional view all relevant information is incorporated into the current yield curve, but according to the microstructure view this is not necessarily so. Since the process of price formation takes time, the yield curve will not completely reflect all available information at any point in time. The assumption that private information becomes incorporated into yields over time suggests that a variable reflecting private information has potential as a predictor of future yield changes. Studies on the predictability of order flow in other asset markets indicate that bond market order flow can have predictive ability for bond yields. In this paper, aggregate interdealer order flow, individual dealer interdealer order flow, and individual dealer customer order flow are used as predictor variables for yield changes. As order flow can contain different types of information relevant for future yield changes over shorter or longer periods, the predictions are conducted both at the daily and the monthly horizon.

4.2 The classical term structure model adapted to short horizon forecasts

The analysis in this paper is based on a simple term structure model widely used to test the expectations hypothesis. The classical expectations hypothesis constitutes the foundation of the literature on interest rate predictability and is described for example in Cochrane (2001). It states that bond yields are expected values of average future short term interest rates and a constant risk premium. This implies that forward rates can predict future interest rate changes. However, traditional term structure models produce poor forecasts of interest rate changes, especially at short horizons. Fama and Bliss (1987) and Campbell and Shiller (1991) reject the expectations hypothesis by documenting that forward rates have little predictive power for future interest rates. Instead they find that forward rates predict the excess return of a bond which is a proxy for the bond risk premium. Cochrane and Piazzesi (2005) confirm these findings by showing that a linear combination of forward rates have strong forecasting power for excess returns on all bonds. These results indicate that bond yields contain time-varying risk premia and that these premia are predictable.

Time-varying bond risk premia also imply that yield changes reflect either changes in expected future short rates or changes in the risk premium. This means that if order flow predicts yield changes, it can predict changes in future short rates or changes in the risk premium. In an attempt to determine this we investigate the predictive power of order flow on both yield changes and bond excess returns. To preserve space only the results for yield changes are presented in the paper, but the results for excess returns are available upon request.

The term structure models used in previous studies are adapted to shorter horizons to fit the nature of the data used in this study. Whereas Fama and Bliss (1987) and Cochrane and Piazzesi (2005) analyze forecasting horizons of one to four years, this paper uses forecasting horizons of one day and twenty days. The twenty day horizon is referred to as the monthly horizon. Daily and monthly yield changes of zero coupon bonds with 1, 2, 3, 4, 5 and 10 years to maturity are predicted by the models presented below. Since the forecasting horizons are short relative to the maturity of the bonds, the yield changes 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 $N\ years - 1\ day \approx N\ years$ and $N\ years - 1\ month \approx N\ years$. Yield changes are calculated according to

$$dy_{t+1}^{(N\ years)} = y_{t+1}^{(N\ years)} - y_t^{(N\ years)}. \tag{1}$$

where $y_t^{(N)}$ is the log yield of a N year zero-coupon bond at day t or month t and $dy_{t+1}^{(N\ years)}$

is the one-period change. Equation (1) shows that daily (or monthly) yield changes are calculated using the same maturity yield.

Fama and Bliss (1987) use the forward spread to test the expectations hypothesis. The forward spread is defined as

$$FS_t^N \equiv f_t^{(N \to N+1)} - y_t^{(1m)}, \tag{2}$$

where FS_t^N is the forward spread at the N year horizon, $f_t^{(N \to N+1)}$ is the forward rate quoted at time t for the one period interest rate from period N to period N+1, and $y_t^{(1m)}$ is the one month zero rate. Equation (2) states that the forward spread is measured as the one period forward rate starting at time N minus today's one period rate.

In order to investigate the predictive power of order flow while controlling for traditional term structure variables, five models are used in the in-sample predictions. Two models, a) and b), are simple term structure models including the Fama-Bliss maturity dependent forward spread defined in Equation (2) and the first three principal components of forward rates respectively. One model, c), is based on lagged order flow only. The last two models, d) and e), include both order flow and the term structure variables. The daily analysis is based on 1505 observations covering the period from September 1999 to September 2005. The first model, model a), uses the Fama-Bliss forward spread as the only predictor variable,

$$dy_{t+1}^{(N\ years)} = \beta_0 + \beta_1 FS_t^N + \epsilon_{t+1}, \tag{3}$$

where $dy_{t+1}^{(N\ years)}$ is the change in the N-year zero yield from day t to day t+1, β_0 is a constant, FS_t^N is the N year forward spread at time t and ε_{t+1} is the error term. The second model, model b), is related to Cochrane and Piazzesi (2005) and uses the principal components of forward rates as explanatory variables,

$$dy_{t+1}^{(N\ years)} = \beta_0 + \sum_{k=1}^{3} \beta_2^k F_t^k + e_{t+1}, \tag{4}$$

where $k = 1, 2, 3$ and F_t^1 is the first principal component, F_t^2 is the second principal component and F_t^3 is the third principal component of forward rates. Model b) is also used in the out-of-sample analysis in order to isolate the predictive power of forward rates. The third model, model c), uses lagged order flow only,

$$dy_{t+1}^{(N\ years)} = \beta_0 + \beta_3^S OF_t^S + \beta_3^M OF_t^M + \beta_3^L OF_t^L + \omega_{t+1}, \tag{5}$$

where OF^S refers to short term order flow, OF^M refers to medium term order flow, and OF^L refers to long term order flow. Model c) is also used in the out-of-sample analysis in order to isolate the predictive power of order flow. Finally, the fourth and fifth models, model d) and model e), include both forward rates and order flow as predictive variables,

$$dy_{t+1}^{(N\ years)} = \beta_0 + \beta_1 FS_t^N + \beta_3^S OF_t^S + \beta_3^M OF_t^M + \beta_3^L OF_t^L + \kappa_{t+1}, \tag{6}$$

$$dy_{t+1}^{(N\ years)} = \beta_0 + \sum_{k=1}^{3} \beta_2^k F_t^k + \beta_3^S OF_t^S + \beta_3^M OF_t^M + \beta_3^L OF_t^L + \nu_{t+1}. \tag{7}$$

Model d), presented in Equation (6), includes the forward spread and order flow as predictive variables. Model e), presented in Equation (7), includes the first three principal components of forward rates and the three order flow groups.

The five regression models presented in equations (3) to (7), are applied for each yield maturity, first to daily data then to monthly data. Recent studies, for example Boudoukh, Richardson and Whitelaw (2008), have shown that long horizon forecasts based on overlapping observations of highly persistent variables may lead to spurious results. In order to avoid some of the possible bias due to the high persistence of monthly order flow based on overlapping observations, this study uses non-overlapping monthly observations. Monthly order flow is constructed by aggregating daily order flow over 20 day periods. The principal components are based on monthly forward rates. The five models presented above are also used for the monthly predictions of yield changes and excess returns.

5 In-sample results based on aggregate order flow

The in-sample results based on aggregate interdealer order flow can be summarized in four main points. First, order flow can predict daily and monthly yield changes. This indicates that order flow can contain different types of information, both non-fundamental information and fundamental information of short or somewhat longer duration. Second, order flow has predictive power in the presence of the forward spread and the first three principal components of forward rates. This implies that bond market order flow contains information about future yield changes that is not yet incorporated into the yield curve. Third, order flow has predictive power across all maturities but tend to be stronger at the short end of the yield curve. This suggests that the information reflected in order flow can be most relevant for the short end of yield curve. Fourth, order flow of all duration groups contains information about future yields and medium term order flow, including trades in bonds with 4 to 7 years to maturity, has the strongest predictive power. These findings are consistent with the market microstructure view that the adjustment of prices to new information does not occur instantaneously, but is incorporated into prices over time through order flow.

5.1 Daily predictions

Table 3 displays the results of the in-sample predictions of yield changes at the daily horizon. The predictions are based on models a) to e) which are presented in equations (3) to (7). The first two models test the predictive power of traditional term structure variables. Model a), which has the Fama-Bliss forward spread as the only predictive variable, does not have any predictive power for daily yield changes. The forward spread has no significant coefficients except for the 1-year yield change. Also model b), which includes the first three principal components of forward rates, has little predictive power. The first and second principal components have no significant coefficients for yields of any maturity. The third principal component of forward rates is significant for 10-year yield changes only.

Model c) is the pure order flow model. The table shows that short, medium or long term order flow has significant predictive power for yield changes of all maturities. The predictive power of order flow is somewhat higher at the short end than at the long end of the yield curve with adjusted R^2s varying from 2.9 to 1.0 percent. Medium term order flow has the most significant predictive power both economically and statistically for all yields except for the 10-year yield. An increase in medium term order flow of one standard deviation (3.7 trades) today will, all other equal, reduce the 3-year yield by 0.44 basis points tomorrow, corresponding to 1,2 percentage points on an annual basis. For 10-year yield changes, only long term interdealer order flow has significant forecasting power.

Model d) includes both the forward spread and order flow as predictive variables. The results in Table 3 show that order flow has significant predictive power in the presence of the Fama-Bliss maturity specific forward spread. The size and significance of the order flow coefficients appear to be unchanged from the pure order flow model when including the forward spread. The results of model e), which includes the three principal components of forward rates and the three order flow groups, confirm the findings of model d). Order flow remains significant when adding forward rates in the predictive regressions. The R^2s of the model for the different maturities vary between 2.8 and 1.2 percent. In all, the results from this model indicate that order flow predicts future yield changes and that the information in order flow is independent of the information imbedded in the current yield curve. However, the low R^2s imply that it can be difficult to use this information profitably when taking transaction costs into consideration, but this is beyond the scope of this paper.

5.2 Monthly predictions

Table 4 displays the results of the in-sample predictions of monthly yield changes. The monthly predictions are based on models a) to e) presented in subsection 4.4 using non-overlapping monthly data.[8] The results of model a), which has the forward spread as the only predictive variable, reveal the same pattern as the corresponding daily model. For all yields except the 1-year yield, the forward spread has no significant predictive power. Model b), which includes the first three principal components of forward rates, has higher forecasting power at the monthly horizon than at the daily horizon. The third principal component is statistically significant across all yields except for the 10-year yield. Model c), which includes order flow only, shows that monthly order flow explains a substantial part of monthly yield changes, with an adjusted R^2 of between 6 and 17 percent across all yields. These in-sample results are in line with Evans and Lyons (2005) who find that the predictive power of lagged order flow increases with the horizon when looking at exchange

[8] Because of the relatively small sample of non-overlapping monthly data, the results are controlled by performing monthly predictions based on overlapping data. The results of the two methods give similar results indicating that there is no small sample bias.

rates. The predictive power of order flow is higher at the short end than at the long end of the yield curve, which is in line with the results at the daily horizon.

At the monthly horizon medium term order flow has significant forecasting power across all yields, whereas long term order flow has no significant coefficients along the yield curve. Short term order flow has predictive power for 1 to 3 year yields. An increase in medium term order flow of one standard deviation will decrease the yield of the 3-year bond with 5.86 basis points, corresponding to 0.7 percentage points on an annual basis, in the following month. The monthly effect is smaller than the daily effect. This could indicate that a substantial part, but not all, of the predictive power in order flow is based on short-lived private information. Model d), which includes both the forward spread and order flow, does not improve the forecasting power relative to model c), which includes order flow only. This confirms that order flow has independent predictive power, and that the forward spread is a poor predictor of yield changes both at the monthly and daily horizon. Model e), combining the principal components of forward rates and order flow, outperforms both model b) and model c) across all yields except for the 10-year yield, with adjusted R^2s increasing from 11.5 percent for the 5-year yield to 18.4 percent for the 1-year yield. This shows that both lagged order flow and forward rates have predictive power at the monthly horizon.

6 Out-of-sample results based on aggregate order flow

The main finding in this section is that the out-of-sample results to a large extent confirm the in-sample results and document that interdealer order flow is a robust predictor of yield changes. The method in Goyal and Welch (2008) is employed to evaluate the out-of-sample performance of order flow and forward rates. The stability of a predictive variable is tested by comparing its out-of-sample forecasts over time to a benchmark model. The benchmark model of Goyal and Welch (2008) uses the historic average of the equity premium as the prediction for the next period. In this paper the benchmark model uses the historic average of changes in the bond yield. This is a version of the random walk model (RW) and can be written as

$$dy_{t+1}^{(N\ years)} = c + \upsilon_{t+1}, \tag{8}$$

where $dy_{t+1}^{(N\ years)}$ is the one period N year yield change, c is a constant and υ_{t+1} is the error term. Equation (8) states that the RW forecast depends on the historic average of yield changes up to period t.

To evaluate the predictive power of order flow and forward rates predictions based on these variables are compared to the predictions of the RW. These comparisons are made separately for order flow and principal components of forward rates. The two models, the order flow model and the pure term structure model, are referred to as the alternative model when compared to the RW. If a variable has no predictive power in-sample, there is no reason to test the variable out-of-sample using the same data set. Consequently only variables which have predictive power in-sample are included in the models compared to the RW. To compare the out-of-sample performance of the alternative model with the RW, the mean squared forecasting errors (MSE) of the recursive forecasts from the two models are calculated. To test whether the MSE of the order flow model is significantly smaller than the MSE of the RW, the McCracken (2007) MSE-F test is employed. This test statistic tests the null hypothesis that the constant yield change model has a MSE that is less than, or equal to that of the time varying yield change model. The alternative hypothesis is that the time-varying model has a lower MSE. The test statistic is

$$MSE - F = (T - h + 1) * (\frac{MSE_R - MSE_U}{MSE_U}), \tag{9}$$

where T is the number of observations in the sample, h is the horizon, MSE_R is the mean squared forecast error of the random walk and MSE_U is the mean squared forecast error of the alternative model being tested. Equation (9) defines the test statistic as the ratio of the difference in the MSE of the model being evaluated and the MSE of the random walk over the MSE of the alternative model times the number of observations.[9] Critical values of this non-standard test are provided in Clark and McCracken (2005).

In order to check that the predictive power of a variable is not due to a special event or time period, Goyal and Welch (2008) monitor the predictive power of the alternative model relative to the benchmark over the whole sample period. They do this by illustrating graphically the cumulative squared prediction errors of the RW model minus the squared

[9] Since the horizon is either one day or one month, and the monthly data are non-overlapping, $(T - h + 1)$ will always be equal to the number of observations in the sample.

prediction errors of the alternative model. In periods when this metric increases, the alternative model predicts better, in periods when it decreases, it predicts worse than the random walk. The same method is employed in this paper to illustrate the performance of order flow and forward rates relative to the RW.

6.1 Daily predictions

Table 5 displays the results of the out-of-sample predictions of yield changes at the daily frequency. The recursive forecasts cover the period from September 2000 to September 2005. The table compares the out-of-sample predictive power of alternative models including order flow or forward rates to the RW. The alternative models only contain variables that are significant in-sample. As a result of this, there are different specifications for the alternative models at each maturity. The first column in Table 5 lists the maturity of the bonds. The second column displays the variables included in the alternative model. The third column displays the ratio of the mean squared errors (MSE) between the alternative model and the RW. The McCracken test statistic is shown in the fourth column. The table documents that the order flow model outperforms the RW model for all maturities. The MSE ratios are all below 1, and the MSE-F test statistics are highly significant. For 1 to 5 year bonds only order flow variables were significant in the in-sample predictions. Thus, in the out-of-sample predictions only order flows are included. For predictions of the 2-year yield, we see that the model including short term and medium term lagged order flow clearly outperforms the RW. The MSE-ratio of 0.98 indicates that the average prediction error of the order flow model is smaller than that of the RW model. Also, the MSE-F test statistic of 22.88 is highly significant.

Figure 1 illustrates the performance of the order flow model including short and medium term order flow versus the RW in predicting daily 2-year yield changes over time. The positive slope indicates that the accumulated MSE of the order flow model is smaller than the accumulated MSE of the RW over the period September 2000 to September 2005. The figure shows that the order flow model did especially well in the fall of 2001 following the 9/11 terrorist attacks. Also, in the spring of 2004, when the easing of monetary policy in Norway came to an end, the order flow model did much better than the RW model. An increasing curve over the whole period indicates that the order flow model predicts better than the RW model over time and implies that the results are not due to a one-time event.

The pure term structure model is tested for the 10-year maturity only. The second and third principal components of forward rates are significant in-sample and included in the out-of-sample term structure model. The MSE-F test statistic is 2.57 for the term structure model compared to 16.45 for the order flow model at this maturity. With a MSE ratio of 1.00 for the term structure model and 0.99 for the order flow model at the 10-year maturity the results clearly indicate that the order flow model outperforms both the term structure model and the RW along the whole yield curve.

6.2 Monthly predictions

Table 6 presents the results at the monthly horizon. The recursive forecasts are based on monthly, non-overlapping data and cover the period from August 2001 to September 2005. The table compares the out-of-sample predictive power of the order flow model and the simple term structure model to the RW. As for the daily predictions, there are different specifications for the alternative models at each maturity since the alternative models contain variables that are significant in-sample only. The table shows that the order flow model clearly outperforms the RW in predicting monthly yield changes along the whole yield curve. The pure term structure model also outperforms the RW in forecasting changes in the 2, 3, 4 and 5-year yields. However, lower MSE-ratios and higher MSE-F test statistics indicate that order flow variables are better predictors than forward rates. While the MSE-ratios for the order flow models are in the range 0.87 to 0.93, the MSE-ratios for the forward rates are in the range 0.95 to 1.0.

Figure 2 illustrates the performance of the order flow model and the pure term structure model in predicting monthly changes in the 2-year yield versus the RW over time. The order flow model includes short and medium term order flow. The positive slope indicates that the accumulated MSE of the order flow model is smaller than the accumulated MSE of the RW over the period September 2001 to September 2005. The figure shows that the order flow model did especially well from 2001 to 2003. The term structure model includes the third principal component of forward rates only. The negative slope in 2002 indicates that the pure term structure model in some periods performs worse than the RW model. The difference in the slopes for the order flow model and the pure term structure model documents that order flow outperforms forward rates as a predictive variable. This indicates that order flow contains more information about future monthly yield changes than the current yield curve.

7 The source of predictability - individual dealers

The results from the previous section document that aggregate interdealer order flow has predictive power for yield changes at daily and monthly horizons. This section investigates two possible sources of predictive power in interdealer order flow. The first is informed customer trades and the second is dealer skill in collecting and processing other relevant information. The unique data set used in this study, including customer trades and interdealer trades of individual dealers, enables the direct identification of the two sources. If both the interdealer and customer order flow of a dealer can predict yield changes, informed customer trades are the likely source of information. If only the interdealer order flow of a dealer can predict yield changes, dealer skill is a likely source of information.

Seven dealers, representing about 85 percent of the trades in the data set, are included in this part of the analysis.[10] These seven dealers are banks and brokerage houses who have been trading in government bonds throughout the whole sample period, many of them as primary dealers. In order to investigate and compare the predictive power of the order flow of the seven dealers, the following model is employed for each dealer and each yield maturity at the daily and monthly horizons:

$$dy_{t+1}^{(N\ years)} = \beta_0 + \sum_{k=1}^{3} \beta_2^k F_t^k + \sum_{j=S}^{L} \beta_3^j OF_{i,t}^j + \sum_{j=S}^{L} \beta_4^j COF_{i,t}^j + \varepsilon_{t+1} \tag{10}$$

where $i = 1, 2, 3, 4, 5, 6, 7$ identifies the seven dealers. β_0 is a constant, F_t^k is the kth principal component of forward rates where $k = 1, 2, 3$. $OF_{i,t}^j$ is the interdealer order flow of dealer i where $j = S, M, L$ is short, medium and long term order flow, respectively. $COF_{i,t}^j$ denotes the customer order flow of dealer i at the different maturities. N denotes the yield maturity where $N = 1, 2, 3, 4, 5, 10$ years. Equation (10) shows that the term structure model used in this study includes lagged values of short, medium and long term

[10] The order flow of dealers who are not present in the market for a substantial part of the sample period and dealers who only sporadically traded, are not included in this section.

interdealer order flow and customer order flow for each dealer in addition to the three forward rate factors.

After running the in-sample predictions based on the model in Equation (10), out-of-sample predictions are run with the variables that are significant in-sample. To interpret the results, two assumptions are made. First, if the interdealer order flow of an individual dealer has predictive power, the dealer is considered informed. She could be informed either because she has the ability to identify her informed customer trades or because she has the skill to collect and interpret other available public and private information. Second, if the interdealer order flow of an individual dealer has no predictive power, the dealer is considered uninformed. However, her customer order flow could still have some predictive power. If this is the case, her customers are on average informed. Finally, if neither the interdealer order flow nor the customer order flow of a dealer have predictive power, her customers are on average uninformed.

If a dealer is informed and the source of predictability is informed customer trades, both her customer order flow and her interdealer order flow are expected to have predictive power. The assumption is that dealers will utilize the private information extracted from informed customer trades by trading in the interdealer market in the same direction. If an informed customer buys bonds from Dealer A, Dealer A infers that bonds are undervalued and she will initiate a buy trade from Dealer B. The interdealer order flow of Dealer A will thus reflect informed customer trades and both her interdealer and customer order flow should have predictive power. If a dealer is informed and the source of predictability is dealer skill, only her interdealer order flow is expected to have predictive power. Dealer skill is defined as the skill in acquiring and interpreting information from other sources than the dealer's customer base. This includes extracting information about future yield changes from macroeconomic indicators, other public information, or from other dealers.

7.1 Dealer characteristics

To investigate the informational differences between dealers, three dealer characteristics are compared. These are size, customer base and dealer activity. Size is measured as a dealer's total market share in the customer market and the interdealer market. The market share in the interdealer market is measured as the share of initiated trades. The customer base is measured as a dealer's market share in the customer market. Dealer activity is measured by two ratios. First, as the value of a dealer's initiated interdealer trades over the value of her customer trades. Second, as the number of initiated interdealer trades, referred to as active trades, relative to the number of interdealer trades initiated by other dealers, referred to as passive trades. A high ratio characterizes an active dealer and a low ratio a passive dealer.

Dealer activity can indicate whether a dealer is informed or not. A dealer initiating a trade is considered impatient as she chooses to accept the current bid or offer price in order to make sure that the transaction takes place immediately.[11] A dealer who is impatient is likely to possess private information that she wants to utilize before other dealers learn about it.[12] A high share of initiated interdealer trades relative to customer trades and passive interdealer trades may thus indicate that a dealer has information about future yields acquired through informed customer trades or through skill in collecting and interpreting other information. Conversely, a low share of initiated interdealer trades may indicate that a dealer does not possess private information.

Table 7 Panel A and Panel B present the characteristics of the seven dealers. The measures in Panel A are based on the value of trades in NOK while the measures in Panel B are based on the number of trades of each dealer. In Panel A the dealers are listed according to size in Column 1 starting with the largest dealer. The total market share of each dealer is displayed in the second column. There are four large dealers, Dealer 1 to Dealer 4, with market shares ranging from 17 to 24 percent, constituting 85 percent of the market. Of the remaining three dealers Dealer 5 is a medium size dealer, while Dealer 6 and Dealer 7 are small dealers. The third column shows the size of each dealer's customer base measured as their market share in the customer market. The four large dealers also have the largest customer bases. If customer trades are an important source of predictability, these four dealers should be the best predictors, especially Dealer 1 and Dealer 2 with a customer market share of around 25 percent each. The fourth column in Panel A displays the first measure of dealer activity. Among the four large dealers it

[11] Correspondingly, a dealer who is placing a limit order can be considered more patient as she is more concerned about transacting to the "right" price than to make sure that the trade actually will take place.

[12] This is in line with the findings of Osler (2009) in the foreign Exchange market.

varies between 19 and 42 percent.[13] If the relative number of initiated interdealer trades indicates whether a dealer is informed, one would expect the order flow of dealers with a high ratio to predict better than the order flow of dealers with a low ratio. One of the large dealers, Dealer 2, differs substantially from the others by displaying low dealer activity. This can indicate that Dealer 2 is a passive dealer.

Table 7 Panel B displays the total number of trades entered into by each dealer sorted by active interdealer trades, passive interdealer trades and customer trades. As in Panel A, the first column lists the dealers according to size. The second column shows the number of active interdealer trades as a percentage of the total number of trades by each dealer. The second column shows the number of passive interdealer trades as a percentage of the total number of trades by each dealer. The third column shows the number of customer trades as a percentage of the total number of trades by each dealer. The second measure of dealer activity is the ratio of active to passive interdealer trades, but is not shown explicitly. The table shows that Dealer 1 has a high ratio and Dealer 2 a low ratio. Dealer 3 and Dealer 4 have ratios in between, but close to Dealer 1. The medium and small dealers appear to be active dealers.

7.2 Results based on individual dealer order flow

The findings based on individual dealer order flow suggest that dealer skill in collecting and interpreting relevant information is an important source of predictability in addition to informed customer trades. The results document that dealers are heterogeneous and that some dealers have forecasting ability at both daily and monthly horizons. The results further indicate that the predictive power of order flow is not related to dealer size or customer base, but rather to dealer activity. At the daily horizon both customer trades and dealer skill appear to be important sources of information. At the monthly horizon customer order flow is not significant out-of-sample for the informed dealers, indicating that dealer skill is the main source of predictability at this horizon. Among the four large dealers Dealer 2 has the largest customer base but her interdealer order flow has no forecasting ability on either the daily or monthly horizon. Also, Dealer 2 has a much

[13] One very small dealer has a ratio of more than 400 percent indicating a very small customer base and a lot of proprietary interdealer trading.

lower score on the activity measures than the others. However, at the monthly horizon, the customer order flow of Dealer 2 has some predictive power. This suggests that Dealer 2 has some informed customers, but is unable to identify these customers, which is in line with the definition of an uninformed passive intermediary. The findings thus confirm our expectations that active dealers possess private information about future yield changes that is reflected in their interdealer order flow while passive dealers have no such information.

7.2.1 In-sample results

The in-sample results for each dealer are based on the model in Equation (10) and presented in Table 8 to Table 11. Tables 8 and 9 display the results for daily yield changes. Table 8 includes 1 to 3 year yield changes and Table 9 includes 4 to 10 year yield changes. The results show that the predictive power varies substantially between dealers, also between dealers of equal size. The order flow of Dealer 1, which is among the four largest dealers, has the strongest predictive power. The predictive power of Dealer 1 order flow, which is mainly due to short and medium term interdealer order flow, varies between 2.2 and 1.3 percent at the daily horizon. It should be noted that also the medium term customer order flow of Dealer 1 has significant forecasting power for 2 to 5 year yield changes, indicating that informed customer trades can be an important source of information in interdealer order flow. At the long end of the yield curve the long term interdealer and customer order flow of Dealer 1 has significant forecasting power.

The order flow of Dealer 4, who is another large dealer with a large customer base, has the second strongest predictive power. The predictive power of Dealer 4 order flow is due to long term interdealer order flow and the explanatory power varies between 0.4 and 1.2 percent and is highest for 10 year yield changes. It should be noted that the customer order flows of Dealer 4 are insignificant for all maturities at the daily horizon. This suggests that dealer skill is the source of predictability for this dealer. Also, the medium term interdealer order flow of Dealer 5, which is a medium size dealer, has predictive power for 1 to 4 year yield changes. The customer order flow with corresponding maturity has no predictive power. Table 7 Panel B shows that this dealer has a much higher share of active interdealer trades than passive interdealer trades. This points to Dealer 5 as an informed, active dealer who initiates trades to benefit from her private information which is due to her skill in collecting and processing relevant information.

The interdealer order flows of Dealer 2, Dealer 3, Dealer 6 and Dealer 7 have no predictive power at the daily horizon for maturities less than 10 years. The short term customer order flow of Dealer 2 has some predictive power for 1 and 2 year yield changes. The results for this dealer are consistent with her low scores on the dealer activity measures. Dealer 2 appear to be a passive intermediary who is uninformed but has customers who on average are informed about yield changes at the short end of the yield curve.

Tables 10 and 11 display the results for monthly yield changes. Table 10 includes 1 to 3 year yield changes and Table 11 includes 4 to 10 year yield changes. The results are based on the model in Equation (10) with monthly data for each dealer. The three forward factors are included in the models for the individual dealers and the third principal component has some predictive power for 2 to 5 year yields at the monthly horizon. Dealer 1 appears to be the best predictor at the monthly horizon also. The short and medium term interdealer order flow and short term customer order flow of Dealer 1 explain from 9.5 to 13.3 percent of the next month changes in 1 to 10 year yields. Dealer 3 is the second best predictor at the monthly horizon. The short and medium term interdealer order flow, and long term customer order flow for the longer maturities, of Dealer 3 explain from 1.1 to 9.3 percent of monthly yield changes. Dealer 4's short term interdealer order flow has predictive power from 1.9 to 5.1 percent and is strongest at the long end of the yield curve. Dealer 2's short term interdealer and medium term customer order flow have predictive power for monthly yield changes from 3.6 to 7.6 percent in the in-sample predictions. Dealer 5's short term interdealer order flow has predictive power at the mid segment of the yield curve. The small dealers have little predictive power at the monthly horizon. The results at the monthly horizon indicate that some dealers possess private information about future yield changes at the monthly horizon as well.

7.2.2 Out-of-sample results

Table 12 and Table 13 display the out-of-sample results at the daily and monthly horizon, respectively. As in the previous section, only variables that are significant in-sample are included. To separate the effects of interdealer and customer order flow, these order flow variables are tested separately against the RW. Table 12 reveals that the lagged interdealer order flow of Dealer 1 has the strongest out-of-sample predictive power at the daily horizon. The MSE ratios are well below 1 and the MSE-F test statistic is significant at the 1 percent level for all yield maturities. Both short and medium interdealer order flow and medium term customer order flow can predict out-of-sample. Figure 3 illustrates the predictive power of the order flow of Dealer 1 for daily 3 year yield changes. The solid line shows the performance of the interdealer order flow model of Dealer 1 against the RW and the dotted line shows the performance of the customer order flow model. The figure shows that both models outperform the RW and that interdealer order flow has the strongest predictive power. This suggests that informed customer order flow is an important source of information for this dealer, in line with the assumptions outline above. It further suggests that Dealer 1 use her ability to identify informed customers from her customer base, as her interdealer order flow is more informative than her customer order flow.

The table further shows that the interdealer order flow of Dealer 4 has out-of-sample predictive power for daily yield changes along the whole yield curve. For 10 year yields the long term interdealer order flow of Dealer 4 produces the best out-of-sample predictions. However, her customer order flow has no out-of-sample predictability. Figure 4 illustrates the predictive power of Dealer 4 order flow for daily 3 year yield changes. The solid line shows the performance of the long term interdealer order flow of Dealer 4 against the RW and the dotted line shows the performance of the long term customer order flow. The figure shows that while the interdealer order flow model clearly outperforms the RW the customer order flow model does not. This suggests that the source of predictability of Dealer 4 is something other than customer trades which in this paper is referred to as dealer skill in acquiring and processing relevant information. Also, the medium term interdealer order flow of Dealer 5 has out-of-sample predictive power for 1 - 5 year yield changes. As Dealer 5's customer order flow has no out-of-sample predictability, the source of predictability appears to be dealer skill for this dealer also.

The interdealer order flows of Dealer 2, Dealer 3, Dealer 6 and Dealer 7 have no out-of-sample predictive power at the daily horizon. The customer order flow of Dealer 2 and Dealer 3 can predict at the very short end of the yield curve, but the MSE ratios are 1 indicating that the customer order flow models of these dealers are not substantially better than the RW. The results indicate that only two of the seven dealers, Dealer 1 and

Dealer 4, possess information about next day yields. Figure 5 illustrates the difference in the predictive power of the order flow of an informed large dealer and an uninformed large dealer for daily 3 year yield changes. The figure shows the performance of the Dealer 1 short and medium term interdealer order flow model against the RW (solid line) and the performance of the Dealer 2 short and medium term interdealer order flow model against the RW (dotted line). The performance measure for Dealer 1 is an upward sloping curve over the period as a whole. This means that the model based on Dealer 1 interdealer order flow outperforms the RW. The measure for Dealer 2 initially falls and then remains constant for the rest of the period. This indicates that the model based on Dealer 2 interdealer order flow is outperformed by the RW. Figure 5 clearly illustrates that while the order flow of Dealer 1 contains information about next day yield changes, the order flow of Dealer 2 does not. Table 7 Panel A shows that while Dealer 1 and Dealer 2 are both large dealers with a large customer base, each with a 25 percent total market share and a 25 percent customer market share, they score very differently on the activity measure. Dealer 1 has a high score, characterizing an active dealer, and Dealer 2 has a low score, characterizing a passive dealer. This indicates that the predictive power of interdealer order flow is related to dealer activity rather than to customer base.

Table 13 displays the out-of-sample results at the monthly horizon. The interdealer order flow of the large dealers, except Dealer 2, have out-of-sample predictive power. The medium term interdealer order flow of Dealer 1 is the best predictor for monthly yield changes. The MSE ratios of this model are close to 0.90 and the MSE-F test statistics are significant at the 1 percent level. However, the short term customer order flow that was significant in-sample has no out-of-sample predictive power. Also the short and medium term interdealer order flow of Dealer 3, which has no predictive power at the daily horizon, has out-of-sample predictive power for 1 to 4 year yield changes. Finally, the short term order flow of Dealer 4 has significant out-of-sample predictive power along the whole yield curve, especially at the long end. For 10 year yield changes the monthly long term customer order flow of Dealer 4 also has some predictive power.

The interdealer order flow of Dealer 2 has out-of-sample no predictive power at the monthly horizon. This demonstrates how important it is to examine the out-of-sample predictability for a variable even if it is significant in-sample. However, the medium term customer order flow has some predictive power. Table 13 shows that the MSE-F test statistics are significant at the 10 percent level. The short term interdealer order flow Dealer 5 has predictive power for 1 to 3 year monthly yield changes. The order flow of the two small dealers have no predictive power at the monthly horizon.

The results of Dealer 1, 3 and 4 suggest that they are informed dealers as their interdealer order flow can predict monthly yield changes. This is consistent with the relatively high scores of these dealers on the measures of dealer activity displayed in Table 7. As their customer order flow has little or no predictive power at the monthly horizon the results in this paper indicate that their source of information for monthly yield changes to a large extent is dealer skill. The results for Dealer 2 are in line with the results expected for an uninformed dealer who has customers that on average are informed. This is also consistent with the low scores of Dealer 2 on the measures of dealer activity in the interdealer market. A low score indicates that the dealer is a passive intermediary and thus uninformed about future yield changes.

8 Conclusion

This paper makes three contributions. First, it includes bond market order flow as a predictive variable in a term structure model. The results document that lagged interdealer order flow has significant forecasting ability for yield changes beyond the predictive power of forward rates. This implies that order flow contains information about future yield changes that is not yet incorporated into the yield curve. The information in order flow can be of fundamental or non-fundamental character and the results are thus in line with Ludvigson and Ng (2009) who find that macroeconomic factors have forecasting power for bonds. Second, the paper explores dealer heterogeneity. The results show that the order flow of some dealers can predict next day or next month yield changes, while the order flow of other dealers have no predictive power. This finding is contrary to the assumption in many market microstructure models, for example Glosten and Milgrom (1985), that dealers (market makers) are homogenous with access to the same information. However, it is in line with the price leadership effect documented by Peiers (1997) and Sapp (2002). Predictability appears to be related to whether the dealer is passive or active in the interdealer market and not to dealer size and customer base.

The third contribution of this paper is to investigate whether dealer skill can be a source of predictability in interdealer order flow. Traditional microstructure models implicitly assume that informed customer trades is the only source of private information for a dealer. Through a unique data set, including customer trades and interdealer trades of individual dealers, this paper can directly measure whether the customer order flow of a dealer has predictive power. If this is the case, we conclude that informed customer trades is the source of predictability. If not, dealer skill in acquiring and interpreting relevant public and private information can be a source. The results show that both informed customer trades and dealer skill can be sources of predictability. This is consistent with Anand and Subrahmanyam (2008) who find that dealers actively seek and aggregate information in the markets, Green (2004) who document that interdealer trading increases after macro news, and with Menkveld et al. (2011) who conclude that dealers rely on their customer order flow after macro announcements to discover the full price impact.

Order flow also predicts bond excess returns. Order flow has roughly the same predictive power for excess returns and yield changes when controlling for the effect of forward rates. The results for bond excess returns are not included here, but available upon request. Taken together, the findings in this paper suggest that order flow predicts bond risk premia, but risk premia beyond, and perhaps different from, those predicted by forward rates.

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Table 1

Panel A: Principal components analysis of forward rates

The table displays the principal components of the one-month forward rates 1, 2, 3, 4, 5 and 10 years ahead for the period September 1999 to September 2005. The first and second columns show the components and their value ranked according to importance. The third column shows how much each component explains of the total variation in forward rates. The fourth column shows the cumulative effect and displays that the three first components explain 99,9 percent of the variation in forward rates. The fifth column reports the persistence of the components measured by the first order autocorrelation.

Principal component	Value	Proportion	Cumulative proportion	AR(1)
$F1$	5.569	0.928	0.928	0.997
$F2$	0.398	0.066	0.994	0.991
$F3$	0.030	0.005	0.999	0.892
$F4$	0.004	0.001	1.000	0.893
$F5$	0.000	0.000	1.000	0.881
$F6$	0.000	0.000	1.000	0.876

Panel B: Loadings of principal components of forward rates

The table presents the loadings of the first three principal components extracted from the six forward rates. The first component loads about equally on all rates and is positive, and corresponds to the level factor described by Litterman and Scheinkman (1991). The second and third principal components are similar to the slope and curvature factors.

	$F1$	$F2$	$F3$
$f_t^{(1\ year \to 1\ year+1m)}$	0.388	0.630	0.403
$f_t^{(2\ years \to 2\ years+1m)}$	0.410	0.391	-0.046
$f_t^{(3\ years \to 3\ years+1m)}$	0.422	0.074	-0.347
$f_t^{(4\ years \to 4\ years+1m)}$	0.420	-0.189	-0.390
$f_t^{(5\ years \to 5\ years+1m)}$	0.412	-0.355	-0.258
$f_t^{(10\ years \to 10\ years+1m)}$	0.396	-0.532	0.705

Table 2

Panel A: Descriptive statistics for daily bond market and order flow variables

The table presents the number of observations and descriptive statistics for daily yield changes in 1, 2, 3, 4, 5, and 10 year zero coupon bonds, short, medium and long term aggregate interdealer order flow, the three first principal components of forward rates, and the Fama-Bliss forward spread over the period September 1999 to September 2005. The last column displays the first order autocorrelation for the variables.

Series	obs	mean	std.dev.	minimum	maximum	AR(1)
dy1	1504	-0.002	0.044	-0.37	0.25	0.156
dy2	1504	-0.002	0.052	-0.46	0.31	0.139
dy3	1504	-0.002	0.053	-0.49	0.29	0.107
dy4	1504	-0.002	0.052	-0.46	0.29	0.087
dy5	1504	-0.002	0.050	-0.42	0.29	0.082
dy10	1504	-0.002	0.046	-0.24	0.21	0.095
OF^S	1504	-0.75	3.77	-27	22	0.154
OF^M	1504	-0.17	3.69	-26	28	0.066
OF^L	1504	-1.30	4.46	-34	20	0.113
$F1$	1504	-0.00086	2.36	-5.16	3.76	0.997
$F2$	1504	0.00024	0.63	-1.44	1.37	0.991
$F3$	1504	0.00002	0.17	-0.91	0.95	0.892
fwd spread1	1504	0.030	0.75	-2.08	1.52	0.990
fwd spread2	1504	0.252	1.18	-1.90	2.62	0.997
fwd spread3	1504	0.480	1.48	-1.80	3.43	0.998
fwd spread4	1504	0.640	1.66	-1.84	3.91	0.999
fwd spread5	1504	0.740	1.76	-1.86	4.21	0.999
fwd spread10	1504	0.875	1.85	-1.94	4.45	0.998

Panel B: Unconditional correlations daily data

The table presents the unconditional correlations of the order flow variables and the three first principal components of forward rates on a daily basis. The order flow variables include short, medium and long term aggregate interdealer order flow.

	OF^S	OF^M	OF^L
OF^S	1.000		
OF^M	0.241	1.000	
OF^L	0.190	0.235	1.000
$F1$	-0.093	-0.006	-0.087
$F2$	-0.033	-0.025	0.041
$F3$	0.064	0.029	0.054

Table 3
In-sample predictions of daily yield changes

The table displays the results of the in-sample predictions of yield changes at a daily horizon based on models a), b), c), d) and e) for the period September 1999 to September 2005, where $dy_{t+1}^{(i\ y)}$ is the daily yield change of the i year bond , FS_t is the forward spread, $F1_t, F2_t$ and $F3_t$ are the first three principal components of forward rates, and OF_t^S , OF_t^M and OF_t^L are short, medium and long order flow. Coefficients are multiplied with 100 and in bold when significant at the 10 percent level. * indicates significance at the 5 percent level or better.

		FS_t	$F1_t$	$F2_t$	$F3_t$	OF_t^S	OF_t^M	OF_t^L	$Adj.R^2$
$dy_{t+1}^{(1\ y)}$	a	$\mathbf{0.58}^{*}$							0.008
		(3.02)							
	b		0.00	0.00	−0.01				0.001
			(0.53)	(1.51)	(−0.64)				
	c					$\mathbf{-0.09}^{*}$	$\mathbf{-0.13}^{*}$	−0.05	0.029
						(−2.05)	(−3.86)	(−1.54)	
	d	$\mathbf{0.54}^{*}$				$\mathbf{-0.08}$	$\mathbf{-0.13}^{*}$	$\mathbf{-0.06}$	0.036
		(2.79)				(−1.78)	(−3.94)	(−1.86)	
	e		0.00	0.00	−0.00	$\mathbf{-0.09}^{*}$	$\mathbf{-0.13}^{*}$	−0.05	0.028
			(0.05)	(1.49)	(−0.28)	(−1.97)	(−3.79)	(−1.59)	
$dy_{t+1}^{(2\ y)}$	a	0.12							0.000
		(0.96)							
	b		−0.00	0.00	0.00				0.000
			(−0.06)	(0.66)	(0.38)				
	c					$\mathbf{-0.09}$	$\mathbf{-0.13}^{*}$	−0.05	0.020
						(−1.74)	(−2.98)	(−1.62)	
	d	0.11				$\mathbf{-0.09}$	$\mathbf{-0.13}^{*}$	−0.06	0.019
		(0.94)				(−1.71)	(−2.93)	(−1.64)	
	e		−0.00	0.00	0.01	$\mathbf{-0.09}$	$\mathbf{-0.13}^{*}$	$\mathbf{-0.06}$	0.018
			(−0.56)	(0.60)	(0.76)	(−1.76)	(−2.95)	(−1.73)	
$dy_{t+1}^{(3\ y)}$	a	0.02							0.000
		(0.19)							
	b		−0.00	0.00	0.01				0.000
			(−0.23)	(0.52)	(1.20)				
	c					−0.07	$\mathbf{-0.12}^{*}$	−0.05	0.014
						(−1.57)	(−2.75)	(−1.32)	
	d	0.02				−0.07	$\mathbf{-0.12}^{*}$	−0.05	0.013
		(0.25)				(−1.31)	(−2.53)	(−1.56)	
	e		−0.00	0.00	0.01	−0.07	$\mathbf{-0.12}^{*}$	$\mathbf{-0.05}$	0.014
			(−0.70)	(0.48)	(1.62)	(−1.39)	(−2.53)	(−1.74)	
$dy_{t+1}^{(4\ y)}$	a	−0.01							0.000
		(−0.11)							
	b		−0.00	0.00	0.01				0.001
			(−0.28)	(0.62)	(1.61)				
	c					−0.04	$\mathbf{-0.12}*$	$\mathbf{-0.05}$	0.011
						(−0.87)	(−2.33)	(−1.77)	
	d	−0.00				−0.04	$\mathbf{-0.12}*$	$\mathbf{-0.05}$	0.011
		(−0.02)				(−0.87)	(−2.33)	(−1.75)	
	e		−0.00	0.00	$\mathbf{0.02}$	−0.05	$\mathbf{-0.12}*$	$\mathbf{-0.06}*$	0.013
			(−0.65)	(0.61)	(1.87)	(−0.97)	(−2.33)	(−1.98)	
$dy_{t+1}^{(5\ y)}$	a	−0.02							0.000
		(−0.28)							
	b		−0.00	0.00	0.01				0.000
			(−0.23)	(0.80)	(1.48)				
	c					−0.02	$\mathbf{-0.11}*$	$\mathbf{-0.06}*$	0.010
						(−0.46)	(−2.20)	(−2.17)	
	d	−0.01				−0.02	$\mathbf{-0.11}*$	$\mathbf{-0.06}*$	0.010
		(−0.18)				(−0.46)	(−2.21)	(−2.14)	
	e		−0.00	0.00	$\mathbf{0.01}$	−0.02	$\mathbf{-0.11}*$	$\mathbf{-0.07}*$	0.012
			(−0.57)	(0.82)	(1.75)	(−0.55)	(−2.20)	(−2.40)	
$dy_{t+1}^{(10\ y)}$	a	−0.07							0.000
		(−1.00)							
	b		0.00	$\mathbf{0.00}$	$\mathbf{-0.02}$				0.003
			(0.04)	(1.68)	(1.90)				
	c					0.03	−0.06	$\mathbf{-0.11}*$	0.013
						(0.74)	(−1.54)	(−4.01)	
	d	−0.19				0.02	−0.06	$\mathbf{-0.10}*$	0.013
		(−1.21)				(0.67)	(−1.50)	(−4.15)	
	e		−0.00	$\mathbf{0.00}$	$\mathbf{-0.01}$	0.03	−0.06	$\mathbf{-0.11}*$	0.016
			(−0.25)	(1.86)	(−1.85)	(0.88)	(−1.45)	(−4.12)	

Table 4
In-sample predictions of monthly yield changes (non-overlapping data)

The table displays the results of the in-sample predictions of yield changes at the monthly horizon based on models a), b), c), d) and e) for the period September 1999 to September 2005, where $dy_{t+1}^{(i\ y)}$ is the monthly yield change of the i year bond , FS_t is the forward spread, $F1_t, F2_t$ and $F3_t$ are the first three principal components of forward rates, and OF_t^S , OF_t^M and OF_t^L are short, medium and long order flow. Coefficients are multiplied with 100 and in bold when significant at the 10 percent level. * indicates significance at the 5 percent level or better.

		FS_t	$F1_t$	$F2_t$	$F3_t$	OF_t^S	OF_t^M	OF_t^L	$Adj.R^2$
$dy_{t+1}^{(1\ year)}$	a	**11.2**∗ (2.57)							0.090
	b		0.00 (0.05)	0.05 (0.98)	**0.16**∗ (2.02)				0.000
	c					**−0.30**∗ (−2.61)	**−0.22**∗ (−2.31)	0.12 (1.21)	0.167
	d	6.58 (1.55)				**−0.24**∗ (−2.34)	**−0.20** (−1.86)	0.07 (0.64)	0.182
	e		−0.01 (−0.59)	0.01 (0.34)	**0.24**∗ (2.15)	**−0.33**∗ (−3.01)	**−0.22**∗ (−2.08)	0.11 (1.03)	0.184
$dy_{t+1}^{(2\ years)}$	a	2.44 (0.82)							0.000
	b		−0.00 (−0.34)	0.02 (0.43)	**0.25**∗ (2.29)				0.001
	c					**−0.23**∗ (−2.12)	**−0.28**∗ (−2.12)	0.07 (0.70)	0.113
	d	0.71 (0.26)				**−0.23**∗ (−2.07)	**−0.27**∗ (−2.04)	0.01 (0.59)	0.101
	e		−0.01 (−0.99)	−0.01 (−0.23)	**0.33**∗ (2.34)	**−0.29**∗ (−2.45)	**−0.28**∗ (−1.99)	0.06 (0.56)	0.154
$dy_{t+1}^{(3\ years)}$	a	0.57 (0.24)							0.000
	b		−0.01 (−0.43)	0.02 (0.42)	**0.28**∗ (2.42)				0.012
	c					**−0.18** (−1.75)	**−0.28** (−1.95)	0.04 (0.41)	0.085
	d	0.01 (0.00)				**−0.18** (−1.74)	**−0.28** (−1.95)	0.04 (0.39)	0.072
	e		−0.01 (−1.02)	−0.01 (−0.14)	**0.35**∗ (2.47)	**−0.24**∗ (−2.07)	**−0.28** (−1.88)	0.02 (0.16)	0.137
$dy_{t+1}^{(4\ years)}$	a	−0.04 (−0.02)							0.000
	b		−0.01 (−0.42)	0.03 (0.55)	**0.27**∗ (2.53)				0.016
	c					−0.15 (−1.48)	**−0.27** (−1.90)	0.02 (0.22)	0.073
	d	−0.26 (−0.14)				−0.14 (−1.49)	**−0.27** (−1.94)	0.02 (0.24)	0.060
	e		−0.01 (−0.92)	0.00 (0.07)	**0.34**∗ (2.61)	**−0.20** (−1.81)	**−0.27** (−1.84)	−0.00 (−0.05)	0.125
$dy_{t+1}^{(5\ years)}$	a	−0.35 (−0.19)							0.000
	b		−0.00 (−0.37)	0.03 (0.71)	**0.25**∗ (2.56)				0.014
	c					−0.12 (−1.29)	**−0.26** (−1.90)	0.01 (0.08)	0.069
	d	−0.44 (−0.26)				−0.12 (−1.29)	**−0.27**∗ (−1.97)	0.01 (0.12)	0.057
	e		−0.01 (−0.84)	0.01 (0.31)	**0.31**∗ (2.74)	−0.17 (−1.60)	**−0.26** (−1.85)	−0.02 (−0.12)	0.115
$dy_{t+1}^{(10\ years)}$	a	−1.09 (−0.69)							0.000
	b		−0.00 (−0.26)	0.06 (1.60)	0.07 (0.90)				0.000
	c					−0.07 (−0.72)	**−0.25** (−1.85)	−0.02 (−0.29)	0.060
	d	−1.09 (−0.71)				−0.06 (−0.67)	**−0.26**∗ (−2.00)	−0.01 (−0.14)	0.055
	e		−0.01 (−0.62)	0.05 (1.61)	**0.11** (1.76)	−0.09 (−0.86)	**−0.23** (−1.69)	−0.06 (−0.61)	0.054

Table 5
Out-of-Sample predictions of daily yield changes

The table compares the out-of-sample predictive power of models based on order flow and models based on forward rates to the random walk (RW) for the period September 2000 to September 2005. Only variables that are significant in-sample are included in the alternative models. The second column lists the variables included in the alternative model. The third column displays the ratio of the mean squared errors of the alternative models, MSE_U, over that of the RW, MSE_R. A ratio less than one indicates that the alternative model outperforms the RW. To test whether the MSE of the model is significantly smaller than the MSE of the RW, the McCracken (2007) MSE-F test is employed. The value of the McCracken test statistic is displayed in the fourth column. Values in bold indicates a significance level of 10 percent, and * indicates significance at the 5 percent level or better. The forecasts are based on recursive estimation.

	Alt. model vs RW	MSE_U/MSE_R	Test statistic
$dy_{t+1}^{(1Y)}$	OF^S, OF^M	0.975	**33.14***
$dy_{t+1}^{(2Y)}$	OF^S, OF^M	0.982	**21.88***
$dy_{t+1}^{(3Y)}$	OF^M	0.990	**12.53***
$dy_{t+1}^{(4Y)}$	OF^M, OF^L	0.991	**11.75***
$dy_{t+1}^{(5Y)}$	OF^M, OF^L	0.989	**11.12***
$dy_{t+1}^{(10Y)}$	OF^L	0.986	**16.45***
	$F2, F3$	1.000	**2.57***

Table 6
Out-of-Sample predictions of monthly yield changes

The table compares the out-of-sample predictive power of models based on order flow and models based on forward rates to the random walk (RW) for the period September 2001 to September 2005. Only variables that are significant in-sample are included in the alternative models. The second column lists the variables included in the alternative model. The third column displays the ratio of the mean squared errors of the alternative models, MSE_U, over that of the RW, MSE_R. A ratio less than one indicates that the alternative model outperforms the RW. To test whether the MSE of the model is significantly smaller than the MSE of the RW, the McCracken (2007) MSE-F test is employed. The value of the McCracken test statistic is displayed in the fourth column. Values in bold indicates a significance level of 10 percent, and * indicates significance at the 5 percent level or better. The forecasts are based on recursive estimation.

	Alt. model vs RW	MSE_U/MSE_R	Test statistic
$dy_{t+1}^{(1Y)}$	OF^S, OF^M	0.874	**7.66***
	$F3$	0.995	0.30
$dy_{t+1}^{(2Y)}$	OF^S, OF^M	0.900	**5.92***
	$F3$	0.967	**1.86**
$dy_{t+1}^{(3Y)}$	OF^S, OF^M	0.925	**4.34***
	$F3$	0.954	**2.54***
$dy_{t+1}^{(4Y)}$	OF^M	0.925	**4.29***
	$F3$	0.952	**2.66***
$dy_{t+1}^{(5Y)}$	OF^M	0.928	**4.15***
	$F3$	0.956	**2.43***
$dy_{t+1}^{(10Y)}$	OF^M	0.934	**3.76***
	$F3$	0.998	0.03

Table 7
Individual Dealers

Panel A: Dealer characteristics

The table describes the seven dealers who were active in the government bond market during the period 1999 to 2005. They are characterized by size, customer base, dealer activity and the impact of their order flow in predicting yield changes. Size is measured as total market share, calculated as the gross value of customer trades and initiated interdealer trades by the dealer as a percentage of the total value of both markets combined. Customer base is measured as the market share in the customer market, calculated as dealer gross value of customer trades as a percentage of total customer trades. Dealer activity is measured as the value of a dealer's initiated interdealer trades over the value of her customer trades.

	Value of trades in Norwegian kroner		
Dealer	Size	Customer base	Dealer activity
	Total market share	Customer market share	$\frac{Interdealer\ trades}{Customer\ trades}$
1	24 %	24 %	31
2	23 %	25 %	19
3	21 %	19 %	42
4	17 %	18 %	28
5	9 %	9 %	33
6	4 %	4 %	30
7	2 %	1 %	435

Panel B: Composition of dealer trades

The table shows the composition of trades for each of the seven dealers during the period 1999 to 2005. The number of trades entered into by each dealer are divided into interdealer trades and customer trades. Interdealer trades are divided into active trades, which are trades initiated by the dealer, and passive trades, which are trades initiated by other dealers. The first column shows the number of active (initiated) interdealer trades as a percentage of the total number of interdealer and customer trades by each dealer. The second column shows the number of passive interdealer trades as a percentage of the total number of interdealer and customer trades by each dealer. The third column shows the number of customer trades as a percentage of the total number of interdealer and customer trades by each dealer.

	Number of trades as a percentage of total number of trades for each dealer		
Dealer	Interdealer trades		Customer trades
	Active	Passive	All
1	24 %	20 %	56 %
2	15 %	23 %	62 %
3	28 %	27 %	45 %
4	22 %	23 %	55 %
5	34 %	23 %	43 %
6	27 %	28 %	45 %
7	55 %	36 %	9 %

Table 8
In-sample predictions of daily 1 - 3 year yield changes at dealer level

The table displays the predictive power of the order flow of individual dealers over the period September 1999 to September 2005. The table presents the results of regressing yield changes on day t+1 on day t short term, medium term and long term order flow of dealer i in the interdealer market (OF) and the customer market (COF). The regressions also include a constant and the three first forward rate factors at time t, but the coefficients are not included in the table. Coefficients are to the e^{-04} and in bold when significant at the 10 percent level and starred when significant at the 5 percent level or better. T-values in parenthesis.

	Dealer	$OF^S_{i,t}$	$OF^M_{i,t}$	$OF^L_{i,t}$	$COF^S_{i,t}$	$COF^M_{i,t}$	$COF^L_{i,t}$	$Adj.R^2$
dy^{1y}_{t+1}	1	$\mathbf{-0.23}^*$	$\mathbf{-0.48}^*$	−0.08	−0.02	−0.13	−0.01	0.022
		(−2.40)	(−2.85)	(−1.06)	(−0.23)	(−1.35)	(−0.08)	
	2	−0.07	−0.12	−0.09	$\mathbf{-0.18}^*$	0.08	0.02	0.006
		(−0.47)	(−1.46)	(−1.03)	(−2.88)	(1.50)	(0.35)	
	3	−0.11	−0.12	−0.06	−0.06	$\mathbf{-0.16}$	−0.02	0.004
		(−0.75)	(−1.42)	(−0.84)	(−0.77)	(−1.80)	(−0.21)	
	4	−0.06	$\mathbf{-0.17}$	$\mathbf{-0.20}^*$	−0.04	0.02	0.04	0.004
		(−0.63)	(−1.75)	(−2.30)	(−0.51)	(0.36)	(0.37)	
	5	−0.13	$\mathbf{-0.16}^*$	−0.11	0.05	−0.14	0.13	0.005
		(−1.24)	(−2.02)	(−0.78)	(0.38)	(−0.89)	(1.22)	
	6	−0.24	−0.13	−0.22	0.06	0.09	0.28	0.003
		(−1.29)	(−0.63)	(−1.19)	(0.33)	(0.46)	(1.61)	
	7	−0.05	−0.07	−0.09	−0.07	0.21	0.33	0.001
		(−0.79)	(−1.03)	(−1.41)	(−0.27)	(0.87)	(1.16)	
dy^{2y}_{t+1}	1	$\mathbf{-0.26}^*$	$\mathbf{-0.53}^*$	−0.07	0.02	$\mathbf{-0.20}$	−0.05	0.019
		(−2.64)	(−3.22)	(−0.74)	(0.15)	(−1.75)	(−0.60)	
	2	−0.15	−0.07	−0.11	$\mathbf{-0.15}^*$	0.06	−0.01	0.001
		(−0.89)	(−0.59)	(−0.95)	(−2.00)	(0.85)	(−0.08)	
	3	−0.06	−0.14	−0.02	−0.09	$\mathbf{-0.19}$	−0.00	0.000
		(−0.32)	(−1.27)	(−0.30)	(−0.86)	(−1.84)	(0.04)	
	4	−0.11	−0.17	$\mathbf{-0.28}^*$	0.03	−0.02	0.01	0.004
		(−0.79)	(−1.52)	(−2.91)	(0.34)	(−0.22)	(0.10)	
	5	$\mathbf{-0.22}$	$\mathbf{-0.18}^*$	−0.12	0.04	−0.21	0.14	0.004
		(−1.73)	(−1.89)	(−0.64)	(0.26)	(−1.36)	(1.10)	
	6	−0.06	−0.10	−0.11	−0.08	0.03	0.26	0.000
		(−0.27)	(−0.52)	(−0.55)	(−0.29)	(0.11)	(1.33)	
	7	0.00	0.02	−0.12	−0.11	0.24	0.40	0.000
		(0.08)	(0.25)	(−1.57)	(−0.32)	(0.94)	(1.02)	
dy^{3y}_{t+1}	1	$\mathbf{-0.24}^*$	$\mathbf{-0.48}^*$	−0.08	0.07	$\mathbf{-0.24}^*$	−0.06	0.017
		(−2.37)	(−3.49)	(−0.79)	(0.57)	(−2.04)	(−0.67)	
	2	−0.15	−0.06	−0.07	−0.09	0.06	−0.01	0.000
		(−0.96)	(−0.45)	(−0.65)	(−1.21)	(0.77)	(−0.13)	
	3	−0.01	−0.15	−0.01	−0.09	$\mathbf{-0.18}$	0.01	0.000
		(−0.04)	(−1.32)	(−0.08)	(−0.89)	(−1.65)	(0.14)	
	4	−0.11	−0.17	$\mathbf{-0.29}^*$	0.07	−0.06	0.02	0.005
		(−0.79)	(−1.50)	(−3.11)	(0.99)	(−0.60)	(0.21)	
	5	$\mathbf{-0.20}$	$\mathbf{-0.20}^*$	−0.11	0.03	−0.20	0.08	0.004
		(−1.70)	(−2.01)	(−0.55)	(0.20)	(−1.31)	(0.63)	
	6	0.02	−0.10	−0.01	−0.22	−0.04	0.17	0.000
		(0.08)	(−0.58)	(−0.07)	(−0.61)	(−0.15)	(1.03)	
	7	0.02	0.06	−0.12	−0.09	0.20	0.30	0.000
		(0.23)	(0.78)	(−1.35)	(−0.24)	(0.82)	(0.69)	

Table 9
In-sample predictions of daily 4, 5 and 10 year yield changes at dealer level

The table displays the predictive power of the order flow of individual dealers over the period September 1999 to September 2005. The table presents the results of regressing yield changes on day t+1 on day t short term, medium term and long term order flow of dealer i. The regressions also include a constant and the three first forward rate factors at time t, but the coefficients are not included in the table. Coefficients are to the e^{-04} and in bold when significant at the 10 percent level and starred when significant at the 5 percent level or better.

	Dealer	$OF^S_{i,t}$	$OF^M_{i,t}$	$OF^L_{i,t}$	$COF^S_{i,t}$	$COF^M_{i,t}$	$COF^L_{i,t}$	$Adj.R^2$
dy^{4y}_{t+1}	1	**−0.21*** (−2.02)	**−0.42*** (−3.33)	−0.10 (−0.94)	0.10 (0.91)	**−0.25*** (−2.19)	−0.07 (−0.77)	0.016
	2	−0.15 (−1.01)	−0.07 (−0.49)	−0.06 (−0.52)	−0.05 (−0.72)	0.07 (0.89)	−0.02 (−0.29)	0.000
	3	0.03 (0.23)	−0.14 (−1.39)	−0.01 (−0.13)	−0.09 (−0.87)	−0.16 (−1.53)	0.03 (0.31)	0.001
	4	−0.08 (−0.61)	−0.17 (−1.51)	**−0.28*** (−3.12)	0.09 (1.21)	−0.07 (−0.73)	0.04 (0.33)	0.007
	5	−0.17 (−1.56)	**−0.20*** (−1.96)	−0.09 (−0.49)	0.04 (0.24)	−0.17 (−1.18)	0.02 (0.19)	0.004
	6	0.07 (0.30)	−0.10 (−0.68)	0.07 (0.37)	−0.20 (−0.63)	−0.00 (−0.01)	0.10 (0.69)	0.000
	7	0.02 (0.23)	0.09 (1.17)	−0.11 (−1.32)	−0.02 (−0.06)	0.18 (0.77)	0.27 (0.61)	0.000
dy^{5y}_{t+1}	1	**−0.18** (−1.76)	**−0.37*** (−3.04)	−0.10 (−1.12)	0.12 (1.20)	**−0.23*** (−2.21)	−0.08 (−0.93)	0.014
	2	−0.15 (−1.09)	−0.08 (−0.57)	−0.06 (−0.54)	−0.03 (−0.40)	0.08 (1.08)	−0.03 (−0.45)	0.000
	3	0.07 (0.51)	−0.14 (−1.56)	−0.02 (−0.31)	−0.08 (−0.82)	−0.15 (−1.48)	0.04 (0.46)	0.001
	4	−0.05 (−0.35)	−0.16 (−1.51)	**−0.28*** (−3.19)	0.08 (1.21)	−0.07 (−0.73)	0.04 (0.39)	0.006
	5	−0.15 (−1.44)	**−0.19** (−1.76)	−0.07 (−0.44)	0.05 (0.35)	−0.15 (−1.07)	−0.02 (−0.14)	0.003
	6	0.10 (0.50)	−0.10 (−0.79)	0.13 (0.78)	−0.21 (−0.71)	0.01 (0.05)	0.05 (0.40)	0.000
	7	0.02 (0.19)	0.11 (1.46)	−0.12 (−1.43)	0.05 (0.16)	0.19 (0.79)	0.33 (0.76)	0.001
dy^{10y}_{t+1}	1	−0.12 (−1.11)	−0.18 (−1.51)	**−0.16** (−1.62)	**0.15** (1.90)	−0.11 (−1.12)	**−0.13** (−1.78)	0.013
	2	−0.21 (−1.42)	−0.06 (−0.50)	−1.02 (−0.64)	0.01 (0.23)	−0.09 (−1.29)	−0.05 (−0.78)	0.007
	3	0.15 (1.59)	**−0.14** (−1.63)	−0.07 (−0.91)	−0.05 (−0.57)	−0.12 (−1.34)	0.09 (1.00)	0.007
	4	0.10 (0.68)	−0.19 (−0.71)	**−0.32*** (−3.95)	0.03 (0.47)	−0.02 (−0.29)	0.02 (0.19)	0.012
	5	−0.12 (−1.21)	−0.10 (−0.79)	−0.02 (−0.18)	0.12 (0.82)	−0.07 (−0.51)	−0.06 (−0.58)	0.003
	6	0.24 (1.18)	−0.09 (−0.71)	**0.27** (1.81)	−0.20 (−0.95)	0.10 (0.57)	−0.04 (−0.34)	0.004
	7	0.02 (0.16)	**0.11** (1.80)	**−0.16** (−1.88)	0.25 (0.81)	0.23 (0.85)	**0.91*** (2.00)	0.012

Table 10
In-sample predictions of monthly 1- 3 year yield changes at dealer level

The table presents the results of regressing yield changes on month t+1 on the short term, medium term and long term order flow of dealer i over the period September 1999 to September 2005. The regressions also include a constant and the three first forward rate factors at time t, but the coefficients are not included in the table. Coefficients are to the $e^{-04}$and in bold when significant at the 10 percent level and starred when significant at the 5 percent level or better.

	Dealer	$OF^S_{i,t}$	$OF^M_{i,t}$	$OF^L_{i,t}$	$COF^S_{i,t}$	$COF^M_{i,t}$	$COF^L_{i,t}$	$Adj.R^2$
dy^{1y}_{t+1}	1	**−0.67***	**−1.43***	−0.38	0.32	−0.39	0.23	0.095
		(−2.28)	(−2.56)	(−0.83)	(1.36)	(−0.85)	(0.70)	
	2	**−0.68**	1.19	0.47	0.16	**−0.90***	−0.05	0.045
		(−1.77)	(1.48)	(1.04)	(0.43)	(−3.09)	(−0.26)	
	3	−0.24	**−1.37***	−0.29	**−0.67**	−0.00	−0.23	0.091
		(−0.86)	(−3.44)	(−0.74)	(−1.66)	(−0.00)	(−0.71)	
	4	**−1.20***	−0.01	0.25	0.11	0.11	0.08	0.019
		(−2.75)	(−0.21)	(0.57)	(0.30)	(0.32)	(0.12)	
	5	−0.28	**−0.64**	−0.19	0.45	−0.19	−0.25	0.000
		(−1.32)	(−1.68)	(−0.26)	(0.50)	(−0.42)	(−0.45)	
	6	−0.36	**−1.62**	−0.08	−0.15	0.45	0.96	0.000
		(−0.42)	(−1.89)	(−0.07)	(−0.13)	(0.57)	(0.84)	
	7	−0.12	0.07	0.06	0.22	−0.68	−1.10	0.000
		(−0.42)	(0.14)	(0.36)	(0.10)	(−0.39)	(0.47)	
dy^{2y}_{t+1}	1	**−0.77***	**−1.47***	−0.13	**0.56**	−0.51	0.13	0.099
		(−1.99)	(−2.22)	(−0.34)	(1.78)	(−0.95)	(0.55)	
	2	**−0.86***	0.64	0.71	0.12	**−0.78***	−0.10	0.036
		(−2.08)	(0.71)	(1.34)	(0.36)	(−2.89)	(−0.37)	
	3	−0.52	**−1.32***	−0.15	−0.57	0.09	−0.46	0.093
		(−1.49)	(−2.86)	(−0.42)	(−1.51)	(0.21)	(−1.16)	
	4	**−1.36***	−0.19	0.00	0.22	0.15	−0.27	0.000
		(−2.66)	(−0.35)	(0.01)	(0.70)	(0.45)	(−0.39)	
	5	**−0.48**	−0.26	−0.40	−0.04	−0.19	−0.54	0.009
		(−1.79)	(−0.61)	(−0.52)	(−0.05)	(−0.40)	(−0.95)	
	6	−0.41	**−1.54**	0.34	−0.14	0.76	0.22	0.000
		(−0.45)	(−1.82)	(0.27)	(−0.10)	(0.96)	(0.19)	
	7	0.18	−0.02	0.01	−1.08	−0.22	−1.24	0.000
		(0.52)	(−0.04)	(0.04)	(−0.46)	(−0.13)	(−0.51)	
dy^{3y}_{t+1}	1	**−0.78***	**−1.34***	0.00	**0.72***	−0.62	0.08	0.113
		(−1.99)	(−2.03)	(0.05)	(2.12)	(−1.14)	(0.43)	
	2	**−0.93***	0.18	0.80	0.05	**−0.66***	−0.11	0.055
		(−2.21)	(0.21)	(1.55)	(0.18)	(−2.74)	(−0.35)	
	3	−0.62	**−1.09***	−0.06	−0.43	0.03	−0.55	0.090
		(−1.58)	(−2.24)	(−0.18)	(−1.21)	(0.06)	(−1.42)	
	4	**−1.38***	−0.14	−0.07	0.23	0.15	−0.50	0.027
		(−2.88)	(−0.26)	(−0.17)	(0.81)	(0.51)	(−0.80)	
	5	**−0.54**	−0.06	−0.44	−0.19	−0.33	−0.63	0.032
		(−1.65)	(−0.13)	(−0.63)	(−0.20)	(−0.69)	(−1.20)	
	6	−0.22	**−1.49**	0.81	−0.04	0.80	−0.29	0.000
		(−0.25)	(−1.85)	(0.67)	(−0.03)	(1.00)	(−0.25)	
	7	0.33	0.01	−0.03	−1.88	0.32	−1.07	0.000
		(0.95)	(0.03)	(−0.12)	(−0.88)	(0.20)	(−0.47)	

Table 11
In-sample predictions of monthly 4, 5 and 10 year yield changes at dealer level

The table presents the results of regressing yield changes on month t+1 on the short term, medium term and long term order flow of dealer i over the period September 1999 to September 2005. The regressions also include a constant and the three first forward rate factors at time t, but the coefficients are not included in the table. Coefficients are to the $e^{-04}$and in bold when significant at the 10 percent level and starred when significant at the 5 percent level or better.

	Dealer	$OF^S_{i,t}$	$OF^M_{i,t}$	$OF^L_{i,t}$	$COF^S_{i,t}$	$COF^M_{i,t}$	$COF^L_{i,t}$	$Adj.R^2$
dy^{4y}_{t+1}	1	$\mathbf{-0.77}^*$	$\mathbf{-1.20}$	0.10	$\mathbf{0.80}^*$	−0.67	0.03	0.125
		(−2.09)	(−1.90)	(0.36)	(2.38)	(−1.28)	(0.18)	
	2	$\mathbf{-0.94}^*$	−0.09	$\mathbf{0.80}$	0.03	$\mathbf{-0.58}^*$	−0.11	0.070
		(−2.25)	(−0.10)	(1.65)	(0.10)	(−2.72)	(−0.36)	
	3	−0.64	$\mathbf{-0.87}$	−0.00	−0.32	−0.05	−0.59	0.081
		(−1.53)	(−1.77)	(−0.01)	(−0.89)	(−0.10)	(−1.61)	
	4	$\mathbf{-1.34}^*$	−0.04	−0.12	0.19	0.15	−0.62	0.044
		(−3.11)	(−0.08)	(−0.30)	(0.72)	(0.56)	(−1.10)	
	5	−0.54	0.02	−0.43	−0.19	−0.50	−0.61	0.040
		(−1.47)	(0.05)	(−0.70)	(−0.22)	(−1.06)	(−1.28)	
	6	−0.02	$\mathbf{-1.49}^*$	1.06	−0.02	0.73	−0.54	0.000
		(−0.03)	(−1.97)	(0.95)	(−0.02)	(0.90)	(−0.47)	
	7	0.39	0.02	−0.07	−2.21	0.91	−0.88	0.000
		(1.11)	(0.04)	(−0.22)	(−1.16)	(0.65)	(−0.42)	
dy^{5y}_{t+1}	1	$\mathbf{-0.76}^*$	$\mathbf{-1.07}$	0.14	$\mathbf{0.83}^*$	−0.69	−0.02	0.133
		(−2.20)	(−1.81)	(0.58)	(2.56)	(−1.38)	(−0.12)	
	2	$\mathbf{-0.92}^*$	−0.23	$\mathbf{0.75}$	0.03	$\mathbf{-0.53}^*$	−0.12	0.076
		(−2.25)	(−0.30)	(1.67)	(0.13)	(−2.80)	(−0.39)	
	3	−0.63	−0.71	0.03	−0.22	−0.12	$\mathbf{-0.59}$	0.070
		(−1.49)	(−1.42)	(0.12)	(−0.61)	(−0.22)	(−1.76)	
	4	$\mathbf{-1.29}^*$	0.05	−0.16	0.13	0.15	−0.65	0.051
		(−3.26)	(0.10)	(−0.44)	(0.56)	(0.59)	(−1.33)	
	5	−0.51	0.05	−0.41	−0.15	−0.66	−0.55	0.040
		(−1.32)	(0.11)	(−0.75)	(−0.18)	(−1.40)	(−1.27)	
	6	0.13	$\mathbf{-1.51}^*$	1.30	−0.05	0.62	−0.64	0.000
		(0.17)	(−2.12)	(1.17)	(−0.04)	(0.74)	(−0.58)	
	7	0.40	−0.00	−0.10	−2.26	1.46	−0.74	0.000
		(1.15)	(−0.00)	(−0.30)	(−1.33)	(1.16)	(−0.39)	
dy^{10y}_{t+1}	1	$\mathbf{-0.73}^*$	−0.65	0.26	$\mathbf{0.83}^*$	−0.68	−0.21	0.108
		(−2.38)	(−1.33)	(0.96)	(2.74)	(−1.44)	(−0.99)	
	2	$\mathbf{-0.80}^*$	−0.43	0.47	0.08	$\mathbf{-0.37}^*$	−0.20	0.036
		(−1.97)	(−0.78)	(1.29)	(0.39)	(−2.52)	(−0.74)	
	3	−0.54	−0.27	0.09	0.03	−0.19	$\mathbf{-0.60}^*$	0.011
		(−1.33)	(−0.51)	(0.31)	(0.09)	(−0.36)	(−2.23)	
	4	$\mathbf{-1.14}^*$	0.28	−0.26	0.01	0.10	$\mathbf{-0.61}^*$	0.046
		(−3.25)	(0.57)	(−0.80)	(0.06)	(0.43)	(−2.31)	
	5	−0.31	−0.04	−0.29	0.01	$\mathbf{-1.04}^*$	−0.42	0.014
		(−0.75)	(−0.09)	(−0.89)	(0.02)	(−2.06)	(−1.20)	
	6	0.42	$\mathbf{-1.42}^*$	1.51	−0.10	0.14	−0.88	0.000
		(0.72)	(−2.41)	(1.58)	(−0.10)	(0.14)	(−0.89)	
	7	0.34	−0.10	−0.18	2.26	$\mathbf{2.90}^*$	−0.58	0.047
		(1.03)	(−0.29)	(−0.55)	(1.64)	(2.95)	(−0.33)	

Table 12
Out-of-Sample predictions of daily yield changes at dealer level

The table compares the predictive power of alternative order flow models to the random walk (RW) over the period September 2000 to September 2005. Only variables that are significant in-sample are included in the alternative models. The first column indicates the maturity of the yield changes. The second column lists the variables included in the alternative interdealer order flow model. The third column displays the ratio of the mean squared errors of the alternative models, MSE_U, over that of the RW, MSE_R. A ratio less than one indicates that the alternative model outperforms the RW. To test whether the MSE of the model is significantly smaller than the MSE of the RW, the McCracken (2007) MSE-F test is employed. The value of the McCracken test statistic is displayed in the fourth column. The last three columns reports the corresponding data for the alternative customer order flow model. Values in bold indicates a significance level of 10 percent, and * indicates significance at the 5 percent level or better. The forecasts are based on recursive estimation.

Maturity	Dealer	Alt. model	$\frac{MSE^U}{MSE^R}$	Test stat.	Alt. model	$\frac{MSE^U}{MSE^R}$	Test stat.
$dy_{t+1}^{(1Y)}$	1	OF^S, OF^M	0.978	**27.91***			
	2				COF^S	0.995	**6.29***
	3				COF^M	1.000	**2.09***
	4	OF^M, OF^L	1.000	**4.56***			
	5	OF^M	1.000	**4.03***			
$dy_{t+1}^{(2Y)}$	1	OF^S, OF^M	0.981	**24.56***	COF^M	0.996	**3.94***
	2				COF^S	1.000	**1.61***
	3				COF^M	1.000	**1.82***
	4	OF^L	0.996	**7.10***			
	5	OF^S, OF^M	0.996	**6.79***			
$dy_{t+1}^{(3Y)}$	1	OF^S, OF^M	0.985	**18.69***	COF^M	0.996	**5.25***
	3				COF^M	1.000	**1.16**
	4	OF^L	0.996	**7.09***			
	5	OF^S, OF^M	0.996	**6.26***			
$dy_{t+1}^{(4Y)}$	1	OF^S, OF^M	0.988	**14.36***	COF^M	0.996	**5.52***
	4	OF^L	0.992	**6.97***			
	5	OF^M	0.996	**4.23***			
$dy_{t+1}^{(5Y)}$	1	OF^S, OF^M	0.991	**11.37***	COF^M	0.996	**5.19***
	4	OF^L	0.996	**7.57***			
	5	OF^M	0.996	**4.20***			
$dy_{t+1}^{(10Y)}$	1	OF^L	1.000	**2.25***	COF^S, COF^L	1.000	**0.83**
	3	OF^M	1.000	0.29			
	4	OF^L	0.989	**13.23***			
	7	$\mathrm{OF}^M,\mathrm{OF}^L$	1.005	-3.88			

Table 13
Out-of-Sample predictions of monthly yield changes at dealer level

The table compares the predictive power of alternative order flow models to the random walk (RW) over the period September 2001 to September 2005. Only variables that are significant in-sample are included in the alternative models. The first column indicates the maturity of the yield changes. The second column lists the variables included in the alternative interdealer order flow model. The third column displays the ratio of the mean squared errors of the alternative models, MSE_U, over that of the RW, MSE_R. A ratio less than one indicates that the alternative model outperforms the RW. To test whether the MSE of the model is significantly smaller than the MSE of the RW, the McCracken (2007) MSE-F test is employed. The value of the McCracken test statistic is displayed in the fourth column. The last three columns reports the corresponding data for the alternative customer order flow model. Values in bold indicates a significance level of 10 percent, and * indicates significance at the 5 percent level or better. The forecasts are based on recursive estimation.

Maturity	Dealer	Alt. model	$\frac{MSE^U}{MSE^R}$	Test stat.	Alt. model	$\frac{MSE^U}{MSE^R}$	Test stat.
$dy_{t+1}^{(1Y)}$	1	OF^S, OF^M	0.885	**6.77***	COF^S	1.020	-1.010
	2	OF^S	1.073	-3.54	COF^M	0.958	**2.31***
	3	OF^M	0.890	**6.44***	COF^S	1.007	-0.35
	4	OF^S	0.962	**1.58***			
$dy_{t+1}^{(2Y)}$	1	OF^S, OF^M	0.906	**5.39***	COF^S	1.025	-1.25
	2	OF^S	1.054	-2.67	COF^M	0.975	**1.33**
	3	OF^M	0.911	**5.05***			
	4	OF^S	0.960	**2.17***			
	5	OF^S	0.959	**2.25***			
$dy_{t+1}^{(3Y)}$	1	OF^S, OF^M	0.918	**4.68***	COF^S	1.026	-1.30
	2	OF^S	1.028	-1.39	COF^M	0.981	**1.00**
	3	OF^M	0.941	**3.26***			
	4	OF^S	0.957	**2.31***			
	5	OF^S	0.958	**2.26***			
$dy_{t+1}^{(4Y)}$	1	OF^S, OF^M	0.923	**4.29***	COF^S	1.025	-1.27
	2	OF^S	1.011	-0.56	COF^M	0.984	**0.84**
	3	OF^M	0.963	**2.02***			
	4	OF^S	0.955	**2.42***			
	5	OF^S	0.961	**2.11***			
$dy_{t+1}^{(5Y)}$	1	OF^S, OF^M	0.928	**4.04***	COF^S	1.025	-1.28
	2	OF^S	1.004	-0.23	COF^M	0.986	**0.76**
	3				COF^L	1.005	-0.28
	4	OF^S	0.953	**2.54***			
$dy_{t+1}^{(10Y)}$	1	OF^S	1.000	0.04	COF^S	1.031	-1.54
	2	OF^S	1.031	-1.55	COF^M	0.996	0.19
	3				COF^L	0.994	0.31
	4	OF^S	0.938	**3.44***	COF^L	0.970	**1.63***

Figure 1: Predicting out-of-sample daily 2 year yield changes using short and medium term aggregate order flow. The curve illustrates the cumulative squared prediction errors of the random walk model minus the squared prediction errors of the order flow model over the period September 2000 to September 2005. The difference in prediction errors is measured along the vertical axis and the time period is measured along the horizontal axis. In periods when the curve increases, the order flow model predicts better, in periods when it decreases, the random walk give the best predictions.

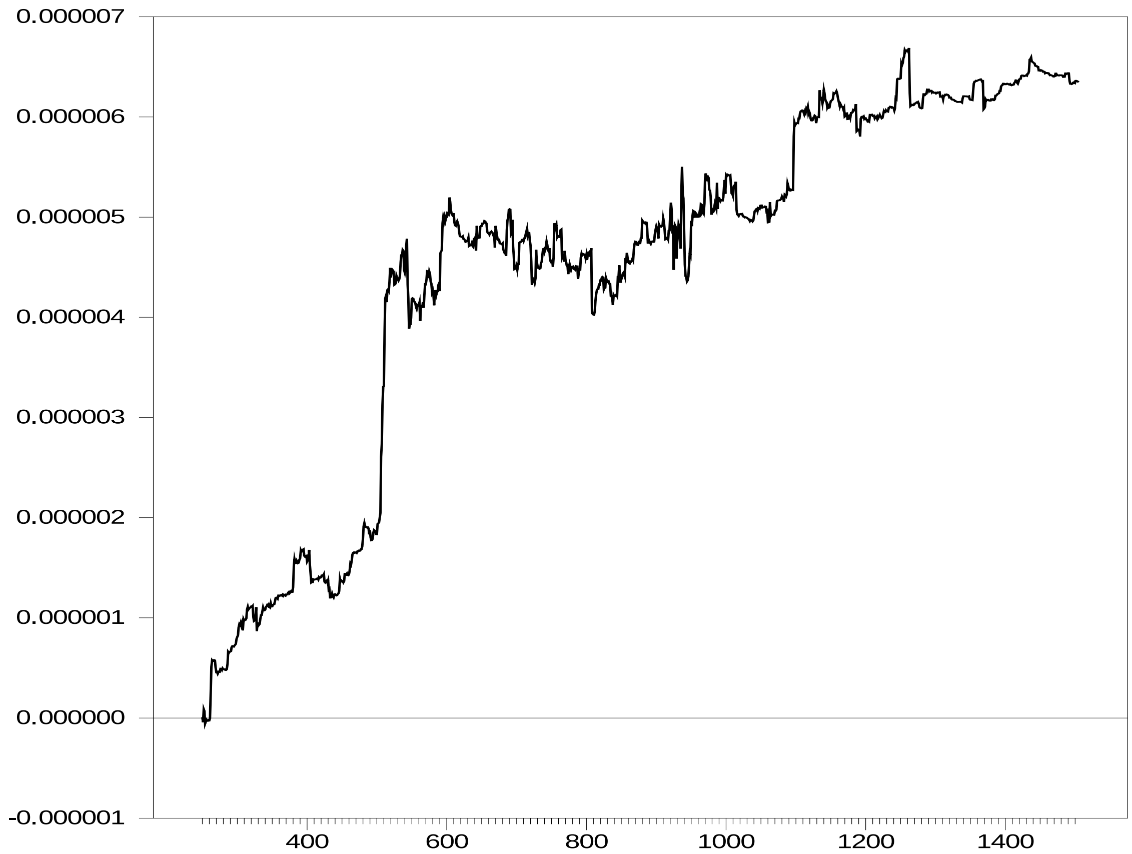

Figure 2: Predicting out-of-sample monthly 2 year yield changes using monthly short term aggregate interdealer order flow and the third principal component of forward rates. The curves illustrate the cumulative squared prediction errors of the random walk model minus the squared prediction errors of the alternative models, the order flow model (solid line) and the term structure model (dotted line), over the period September 2001 to September 2005. The difference in prediction errors is measured along the vertical axis and the time period is measured along the horizontal axis. In periods when the curves increase, the alternative model predicts better, in periods when it decreases, the random walk give the best predictions.

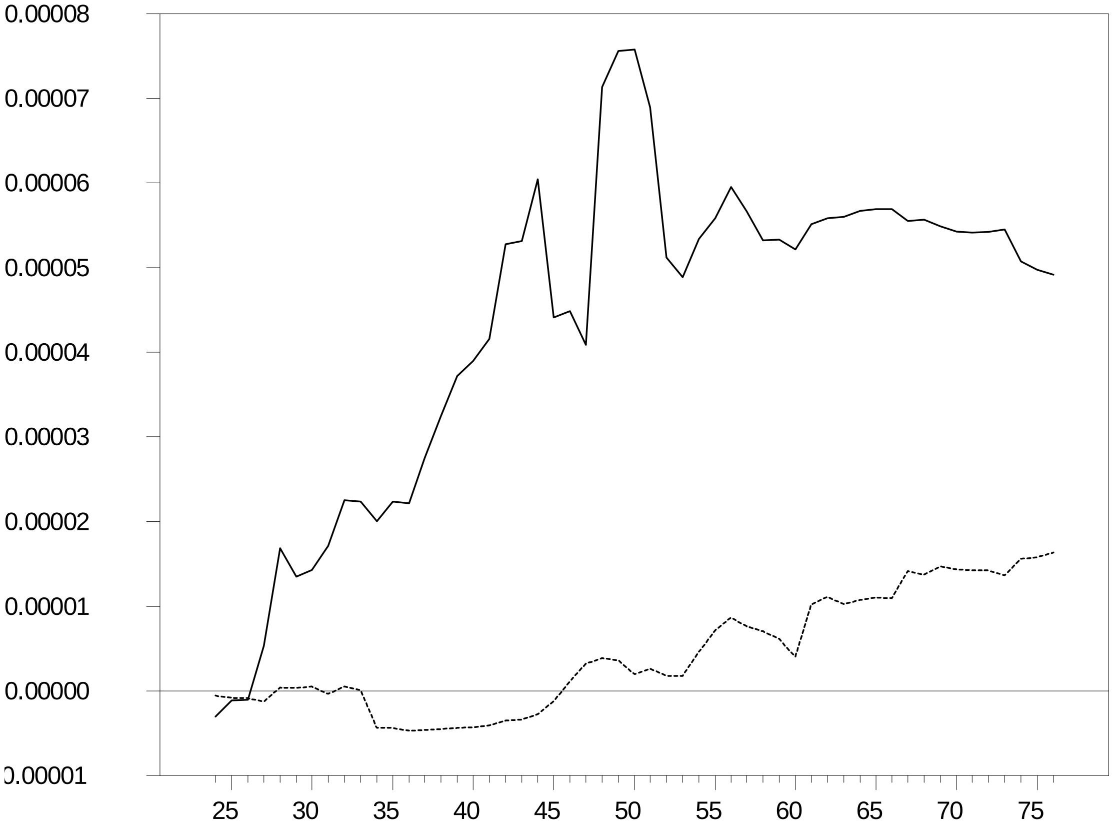

Figure 3: Predicting daily 3 year yield changes using the short and medium term interdealer order flow of Dealer 1 and the medium term customer order flow of Dealer 1. The curves illustrate the cumulative squared prediction errors of the random walk model minus the squared prediction errors of the alternative models, the interdealer order flow model (solid line) and the customer order flow model (dotted line), over the period September 2000 to September 2005. 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 random walk model gives the best predictions.

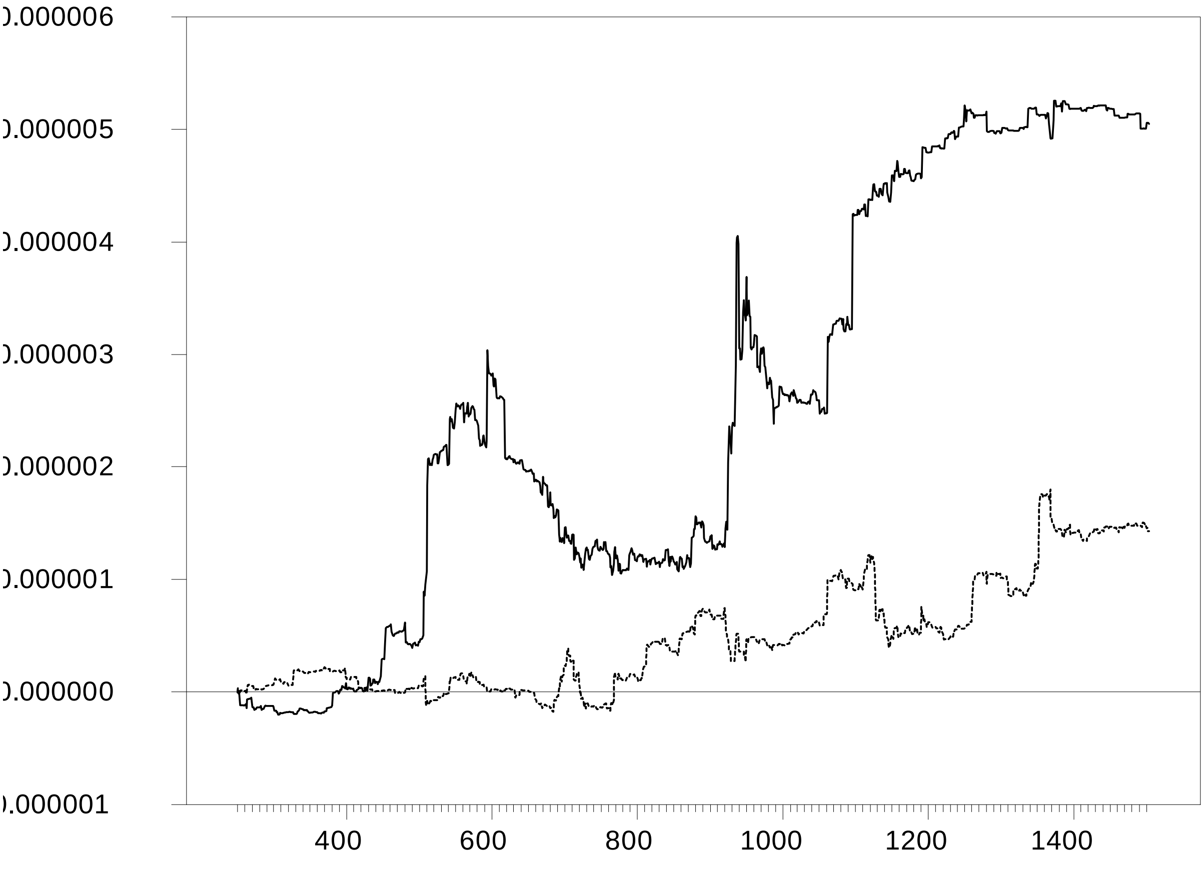

Figure 4: Predicting daily 3 year yield changes using the long term interdealer order flow of Dealer 4 and the long term customer order flow of Dealer 4. The curves illustrate the cumulative squared prediction errors of the random walk model minus the squared prediction errors of the alternative models, the interdealer order flow model (solid line) and the customer order flow model (dotted line), over the period September 2000 to September 2005. 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 random walk model gives the best predictions.

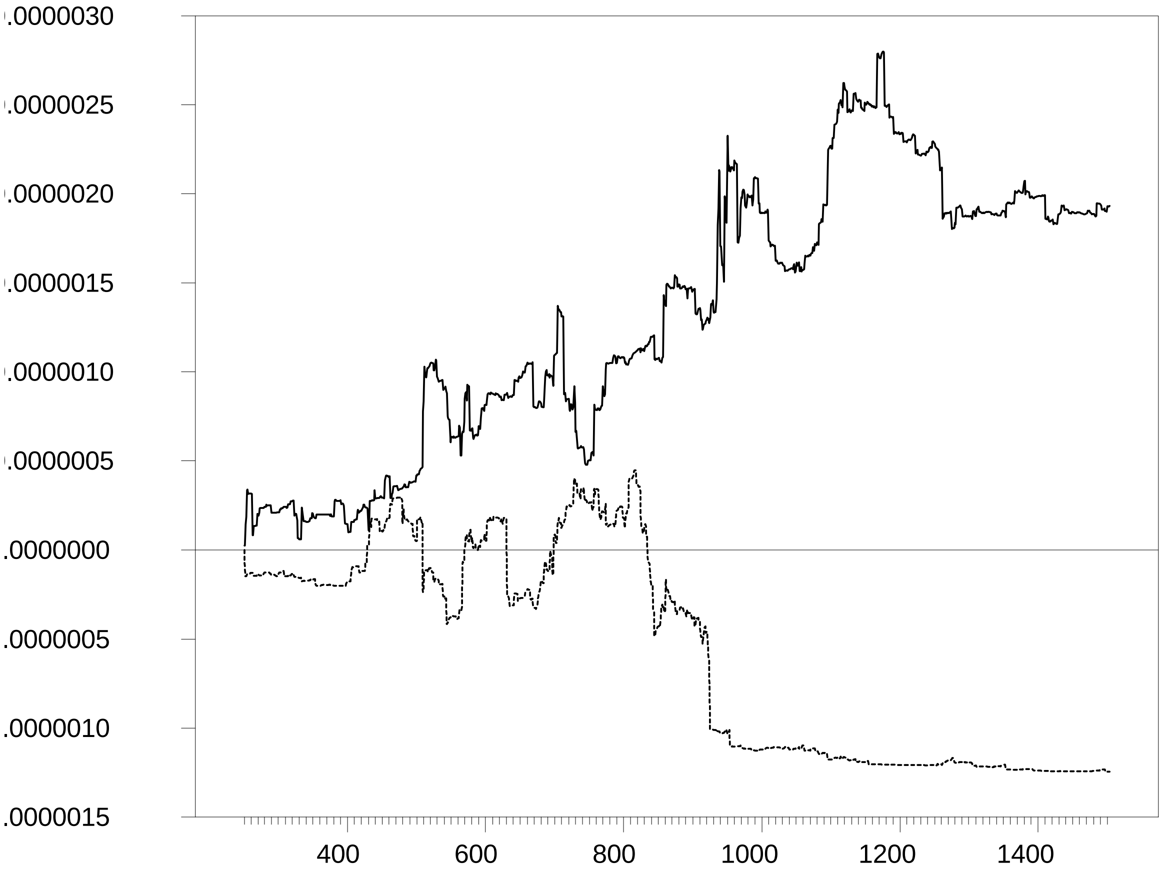

Figure 5: Predicting out-of-sample daily 3 year yield changes using the short and medium term interdealer order flow of Dealer 1 and Dealer 2. The curves illustrate the cumulative squared prediction errors of the random walk minus the squared prediction errors of each interdealer order flow model (solid line for Dealer 1 and dotted line for Dealer 2) over the period September 2000 to September 2005. 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 random walk model gives the best predictions.