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

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Abstract

This paper introduces bond market order flow as a predictor variable in a term structure model and provides evidence that order flow has forecasting ability over and above that of forward rates. Both in-sample and out-of-sample forecasts show that models including interdealer order flow outperform traditional term structure models and the random walk model. This indicates that bond market order flow contains information about future bond prices that is not fully incorporated into the current yield curve. To identify the source of predictability in order flow the paper compares the predictive power of individual dealer order flows. The results, based on a new and detailed data set, show that there are significant differences in the predictive power among dealers. These differences appear to be related dealer activity in the interdealer market and not to the size of their customer base suggesting that they could reflect differences in dealer skill.

Keywords: Term structure, predictability, market microstructure, government bonds.

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1 Introduction

The classical expectations hypothesis implies that forward rates can predict interest rate changes, but empirical studies suggest otherwise. Traditional term structure models produce poor forecasts of interest rate changes, especially at short horizons. Fama and Bliss (1987) and Campbell and Shiller (1991) find that forward rates and yield spreads have little predictive power for future interest rates for horizons up to 2 years. Cochrane and Piazzesi (2005) further strengthen the evidence against the expectations hypothesis. They document that a linear combination of forward rates predicts the bond risk premium. These results have supported the view that interest rates follow a "random walk", indicating that today's interest rate is the best predictor of future interest rates. Recent studies find 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 and yield spreads. Andersen and Benzoni (2010) find that interest rate volatility cannot be extracted from 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 may reflect macroeconomic information, has forecasting power for yield changes. The paper also seeks to identify the source of predictability in order flow by investigating which market participants possess information about future bond yields.

Order flow is defined as the number of buyer-initiated trades minus the number of seller-initiated trades during a day.[1] Order flow is thus a measure of the net buying pressure in the market and may reflect private information about asset prices held by traders. Lyons (2001) defines private information as information not known by all market participants which produces a better price forecast than public information alone. In accordance with this definition, order flow may contain heterogeneous interpretations of macroeconomic indicators as well as other dispersed private information. Dispersed private information can be related to market liquidity, hedging activity and the perception of risk among market participants. In other words, order flow can convey information of fundamental

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

and non-fundamental character held by agents trading in the market. Several market microstructure studies have documented a relationship between order flow and asset price changes. Evans and Lyons (2002), Hasbrouck (1991) and Brandt and Kavajecz (2004) show 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 find that exchange rate forecasts based on order flow clearly outperform forecasts based on macroeconomic variables and the random walk.

This paper makes two main contributions. First, it introduces lagged bond market interdealer order flow as a new variable in a traditional term structure model. Order flow is separated into three order flow variables depending on the maturity of the bonds included in the trades. Second, it employs individual dealer order flow from identified dealers in the predictive regressions to explore dealer heterogeneity. The paper uses a detailed data set from Norway including both the interdealer market and the customer market in government bonds. The data set, covering all trades from September 1999 to September 2005, includes trade types and dealer identities. This enables the paper to 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. These data sets are unable to capture the dynamics between dealers and their customers and are thus unsuitable to explore the role of dealers in the price formation process.

One interesting question, so far unexplored empirically due to a lack of data, is to investigate the sources of predictive power in interdealer order flow. By comparing dealers whose interdealer order flow have different predictive power, the sources of predictability may be identified. If the interdealer order flow of an individual dealer has predictive power it could be because she has passively passed on her informed customer trades to other dealers or because she has obtained information on future yields by using her skill

[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.

in collecting and interpreting available market information. Available market information for a dealer includes public information as well as transactions with customers and other dealers. Two possible sources of predictive power in interdealer order flow are thus customer trades and dealer skill. In this paper dealer skill is defined as the dealer's ability to acquire and correctly interpret public and private information, including the ability to identify informed trades. The two sources of predictability are related to the role of dealers in the price formation process. Are dealers just passive intermediaries executing customer trades or are they actively exerting skill? If dealers whose order flow has predictive power are passive intermediaries, customer trades are expected to be their main source of predictability. If dealers whose order flow has predictive power are actively trading in the interdealer market, dealer skill could be their main source of predictability. This paper explores whether dealer activity in the interdealer market can explain why some dealers are better predictors than others.

There are two sets of results in this study, the first is based on aggregate order flow and the second based on disaggregated order flow. Order flow is disaggregated according to dealer identity and trade type. The first set of results document that models including order flow make better predictions than traditional term structure models. Aggregate interdealer order flow has predictive power over and above that of forward rates. Term structure models including order flow also outperforms 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 0.12 basis points the next day which constitutes 35 basis points on an annual basis. An increase in monthly medium term order flow of one standard deviation, predicts a 0.28 basis point decrease in the 3-year yield in the following month which constitutes 3.4 basis points on an annual basis. The fact that both daily and monthly interdealer order flow have predictive power indicates that it may take up to a month or more for some types of information to become fully incorporated into bond prices. This may reflect, for example, business cycle effects.

The second set of results suggest that the source of predictive power in interdealer order flow can be related to dealer skill in collecting and interpreting relevant information. The results document that individual dealers have different forecasting ability and indicate that dealers with predictive power possess private information unexplained by the size of their customer base. The forecasting ability of individual dealers appears to be related to whether dealers are active or passive in the interdealer market. Active dealers are defined as dealers with a large share of initiated interdealer trades relative to their customer trades and passive dealers as dealers with a low share. Active dealers are more likely to possess private information than passive dealers. Private information can be acquired through dealer skill in obtaining and correctly interpreting relevant information. Further, the proxy for aggregate informed customer order flow has less predictive power than aggregate interdealer order flow, indicating that predictability is related to something else than informed customer trades. Thus, dealer skill and effort could explain why the order flows of some dealers are better predictors of future yield changes than the order flows of others.

Much of the term structure literature focuses on the predictability of bond excess returns, and as a robustness check, the predictive power of order flow on excess bond returns is also calculated. The results show 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. This is consistent with the findings in Ludvigson and Ng (2009).

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. Section 5 reports the in-sample results based on aggregate interdealer order flow. Section 6 reports the out-of-sample results based on aggregate interdealer order flow. Section 7 discusses the source of predictability based on order flow according to trade type and presents the in-sample and out-of-sample results. Section 8 discusses the source of predictability based on individual dealer order flow according to dealer activity and presents the in-sample and out-of-sample results. Finally, section 9 concludes.

2 Related literature

This paper is related to three segments of the finance literature; the market microstructure literature, the term structure literature, and the literature on asset return predictability. Empirical studies on market microstructure have documented that order flow contains information about asset prices. Studies on bond markets include Brandt and Kavajecz (2004) who examine the price formation process in the US Treasury market. They find that up to 26 percent of contemporaneous daily yield changes can be accounted for by interdealer order flow. The yield changes induced by order flow are found to be permanent, and they consequently rule out inventory effects. Green (2004) studies the impact of trading on government bond prices surrounding the release of macroeconomic news. He examines trades that take place in the half hour before and the half hour after the release of a macroeconomic announcement. He 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.

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 when including both news days and no-news days. Aggregate interdealer order flow contains information about yield changes, explaining more than a quarter of daily yield changes, while aggregate customer order flow does not. She further documents that individual interdealer order flow has heterogeneous contributions to contemporaneous yield changes. Underwood (2008) studies the cross-market information content of stock and bond order flow and finds that they play an important role in explaining cross-market returns. This study differs from the above mentioned by focusing on the role of order flow as a predictor of future yield changes.

Predictability based on microstructure models is documented by Evans and Lyons (2005). They find that models including order flow in foreign exchange markets have sig-

[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.

nificant out-of-sample forecasting power for exchange rates. They compare four exchange rate models to the random walk. Two models are based on macroeconomic factors and two models are based on aggregate and disaggregated customer order flow data. They find that while the macroeconomic models are outperformed by the random walk, the microstructure model including the order flow of six customer groups consistently beats the random walk. The forecasts from their model account for nearly 16 percent of the sample variance in monthly exchanges rates. They employ forecasting horizons from one day to one month and use overlapping daily data for horizons exceeding one day. Evans and Lyons (2008) show that order flow forecasts both the exchange rate and its underlying macroeconomic determinants. They conclude that the forecasting relationship arises because the same macro information revealed in order flow is useful for determining the foreign exchange risk premium, generating rational forecastability in returns.

This study is related to Evans and Lyons (2005), but differs in several ways. First, it addresses a different asset market. Second, it uses interdealer order flow instead of customer order flow. Third, it uses individual dealer order flow to investigate possible sources of predictability. Fourth, 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. Finally, while Evans and Lyons (2005) do not test for a possible bias due to the persistence of overlapping observations at the monthly horizon, this paper addresses the potential problem by employing non-overlapping data at the monthly forecasting horizon.

The vast literature on the term structure of interest rates is based on the expectations hypothesis. The classical expectations hypothesis, described for example in Cochrane (2001), states that bond yields are expected values of average future short term rates. It implies that forward rates are expected future spot rates and thus can predict future interest rate changes. It also states that the holding period return on bonds of all maturities should be equivalent. The expectations hypothesis can be modified to include constant risk premia, implying a one-to-one relationship between changes in forward rates and expected future interest rates. However, for the past twenty years empirical studies have produced evidence against the expectations hypothesis, indicating that yields contain time-varying risk premia and that these premia, defined as the expected bond price minus the forward price or the expected excess return on bonds, are predictable.

Fama and Bliss (1987) and Campbell and Shiller (1991) investigate whether forward rates and yield spreads can predict future changes in interest rates, but find little evidence of this. Fama and Bliss (1987) use the forward spread, defined as the one to four year ahead forward one year rate minus the current one year rate, to predict one year yield changes and find that the forward spread is a poor predictor of one year rates, especially at short horizons. They find instead that the forward spread predicts one year excess returns on bonds and conclude that the bond risk premium varies over time and is predictable. Campbell and Shiller (1991) study whether the yield spread, measured as the difference between yields of maturities up to ten years and the short term interest rate, can predict interest rates of all maturities over several horizons. They find that a high yield spread predicts a fall in long yields, which is counter to the expectations hypothesis.

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 with a substantially higher forecasting power than the maturity specific forward spread. The three mentioned studies use monthly observations. Fama and Bliss (1987) use data for the period 1964-1985, Campbell and Shiller (1991) for the period 1952-1987 and Cochrane and Piazzesi (2005) use the Fama-Bliss data updated through 2002 to predict one year excess returns. This study builds on the papers mentioned above by employing forward rates in a simple term structure model. It differs by adding order flow as a predictor variable and by using daily data over forecasting horizons of one day and one month, which is substantially shorter than in earlier studies. In addition to shorter forecast horizons, this study performs out-of-sample forecasting which should be of interest for analysts and investors with short investment horizons.

Kessler and Scherer (2009) extend the Cochrane and Piazzesi (2005) model by applying it to international bond markets, and confirm that the model applies to other markets than the US Treasury market. They find that forward rates predict bond excess returns in seven major bond markets. Engsted and Tanggaard (1995) predict short and long term Danish interest rates using yield spreads for the period 1976-1991, but find that the predictive power of the yield spread disappears under recent monetary policy regimes. They also find that the yield spread predicts long rates in a direction opposite to that implied by the expectations hypothesis. This study adds to the literature on international bond markets by using data from the Norwegian government bond market.

Recent studies highlight the importance of using information beyond that contained in the yield curve to convey the cyclical pattern in bond market risk premia. Several studies find that factors other than forward rates and yield spreads have predictive power for bond risk premia. 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 in-sample and out-of-sample forecasting power. Andersen and Benzoni (2010) find that interest rate volatility cannot be extracted 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. He concludes that wealth dependent relative risk aversion appears to be an important source of bond return predictability. Cooper and Priestley (2008) document that the output gap has predictive power for both stock excess returns and bond excess returns. This study differs from other bond market studies by using a market microstructure variable as a predictor variable. Order flow reflects private information that is not yet incorporated into the yield curve and this information may include heterogeneous interpretations of macroeconomic news, thus supporting the findings of the above mentioned studies.

Finally, this paper is related to the extensive literature on predictability of stock returns. Goyal and Welch (2008) reexamine the performance of variables that have been suggested in earlier studies to be good predictors of the equity premium. They find that most of the models are unstable or even spurious and have predicted poorly, both in-sample and out-of-sample, over the last 30 years. In order to illustrate the performance of a predictor variable over time, they calculate a metric comparing the cumulative squared prediction errors of the model including the predictive variable to that of the random walk. When this metric increases the suggested predictive variable predicts better, when it decreases the random walk predicts better. The same method is used in this paper to illustrate the performance of order flow as a predictive variable relative to the random walk.

Boudoukh, Richardson and Whitelaw (2005) show that for persistent regressors, the estimators are almost perfectly correlated across horizons under the null hypothesis of no predictability. Common sampling errors across equations lead to OLS coefficient estimates and R^2 s that are roughly proportional to the horizon under the null hypothesis of no predictability. This implies that evidence on predictability based on overlapping data may well be spurious. They recommend researchers to be cautious when interpreting long horizon forecasts based on persistent predictors. This paper seeks to avoid any bias due to overlapping observations by using non-overlapping data at the monthly horizon.

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,

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

commercial firms and individuals.

The data set employed in this paper is unique in that it contains data making it possible to distinguish the two markets. 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 are on average around 22 million NOK, and customer trades are on average around 36 million NOK. All trades have to be registered in the OSE electronic trading system within 5 minutes after they are agreed upon. Electronic trades and over-the-counter trades are visible to other traders as soon as they are entered in the electronic order book.

The only exception is delayed publication trades. Dealers can decide to hide their trades from other dealers by choosing delayed publication when registering the trades. These trades will not show up in the system until after a delay. The period of delay and the conditions for delaying a trade have changed during the sample period. In 1999 the delay was 1 hour, and only trades over 200 million NOK were eligible. In 2002 the delay was extended to the end of the trading day, and the size limit was abandoned. The period of delay is granted in order to allow dealers to unwind positions without incurring high costs. By hiding these trades from other dealers, the dealer becomes a temporary monopolist of trade information. The dealer may update her beliefs before the others, and trade before the other dealers get a chance to update their beliefs and adjust their prices. The system of delayed publication thus leads to a less transparent market and information asymmetries may occur.

3.2 Data

The analysis in this paper is based on a comprehensive data set from the Norwegian government bond market. The data set covers the period from September 6, 1999 to September 30, 2005. The number of bonds in the market varies between four to 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 when it is no longer included in the auction calendar, which may be several years after it was first issued.

The data set, kindly provided by Oslo Stock Exchange (OSE), 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, the identity of the buying and the selling dealer, and the type of trade. Different types of trades include auto match (electronic) trades, ordinary over-the-counter trades, non-standard settlement over-the-counter trades, trades registered outside market opening hours, repo trades, delayed publication trades and auction allocations in the primary market.

This study focuses on the predictive power of order flow on yield changes and returns in the secondary market for government bonds. Some trade types are therefore left out when constructing the order flow data. Repo trades, small trades with a trade amount of less than 1 million NOK (180 000 USD) and primary market transactions are excluded from the sample. Repo trades include two opposite trades in the same bond, a sell trade and a buy trade, with different settlement dates. Since the two legs of the repo offset each other, repos are not expected to have any price impact. As the average trade size in the bond market is 35 million NOK, small trades of less than 1 million are assumed to be uninformative.[5] Primary market transactions are not considered relevant for price formation as they are based on uniform price auctions of predetermined volumes. Transactions included in the construction of order flow data are thus ordinary over-the-counter trades, over-the-counter trades with non-standard settlement, delayed publication trades, trades registered outside market opening hours and auto match trades, a total of 66,650 transactions during the sample period.

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).[6] The signed trades

[5] Interdealer trades are normally of a size between 5 and 50 million NOK, but can be smaller and larger. A trade under 1 million would likely be on behalf of a small customer, for example an individual investor. Small customers are not likely to trade on private information.

[6] 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.

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 thus a measure of the net buying pressure in the market. Interdealer order flow is defined as the net buying pressure in the interdealer market. Customer order flow is defined as the net buying pressure in the customer market.

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 bonds with a remaining time to maturity greater than 7 years up to 11 years. Since long bonds gradually increase in size, the bonds included in long term order flow may be somewhat less liquid than the bonds included in the other two categories.

The data set used in this study also includes zero coupon yields and forward rates for Norwegian government bonds, kindly provided by Nordea Markets. 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

In order to limit the number of variables in the predictive regressions the first three principal components of forward rates are employed. Tables 1 and 2 show the decomposition of forward rates into principal components. Table 1 presents the six factors extracted from the one month forward rates maturing in 1, 2, 3, 4, 5 and 10 years. The table 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. Table 2 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. Descriptive statistics based on daily data are presented in Table 3 and on monthly data in Table 4. Table 3 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 of 7 percent. 2, 3, 4 and 5 year yields 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. Excess returns are on average negative due to an inverted yield curve for parts of the sample period.

Table 3 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. The customer order flows based on delayed publication trades have means that are closer to zero, lower standard errors and lower persistence than interdealer order flow. Interdealer order flows orthogonal to these customer order flow, have means close to zero for all three maturities. Finally, Table 3 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.

[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.

Table 4 shows the descriptive statistics for the same variables at the monthly frequency. Yield changes and excess returns are 20 day non-overlapping observations. Order flow is aggregated over 20 day periods. Principal components of forward rates are based on 20 day observations of forward rates. The table displays about the same patterns for monthly data as for daily data for means and standard errors. However, the AR(1) coefficient increases considerably for all series from the daily to the monthly horizon, except for the series on forward rates which are very persistent on both horizons.[8]

The order flow variables employed in this study include interdealer order flow and customer order flow based on delayed publication trades. The latter is used as a proxy for informed customer order flow. Table 5 presents the correlations between the different predictive variables employed at the daily horizon. It appears that short, medium and long term interdealer order flows are positively correlated with a correlation around 20 percent. Short, medium and long term informed customer order flows are also positively correlated with correlations from 3 to 13 percent. These relatively low levels of correlation imply that multicollinearity is not a problem at the daily horizon. Table 6 presents the correlations between the predictive variables at the monthly frequency. The correlation between short and medium term interdealer order flow is higher at the monthly than at the daily frequency, with a positive correlation coefficient of 57 percent. However, the correlation between the other order flow variables is substantially lower. Short and medium term informed customer order flows also exhibit a somewhat higher positive correlation at the monthly frequency. However, multicollinearity do not appear to be a problem at the monthly horizon as the order flow variables are statistically significant in the out-of-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 forma-

[8] The exception is the AR(1) coefficient for the third principal component of forward rates, which actually decreases from 89 percent at the daily horizon to 47 percent on the monthly horizon.

tion over time. According to Lyons (2001) new information is imbedded 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. Whereas the traditional literature assumes that all information is reflected in the yield curve at any point in time, the microstructure literature assumes that some relevant information is not yet incorporated. 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 a proxy for informed customer order flow are used as predictor variables for yield changes. The main sources of private information for a bond dealer are her customer trades and her own skill in obtaining private information. If dealers are passive intermediaries, they will just pass on customer trades to the interdealer market in order to off-load risk and informed customer trades will be the main source of information in their order flow. If dealers are actively seeking and processing relevant private information, dealer skill is likely to be the main source of information in their order flow. One example of dealer skill is when a dealer analyzes and correctly interprets the effects of macroeconomic news. Another example is when a dealer trades actively in the interdealer market and infers private information about changes in the hedging demand of another dealer's customer. By observing the trading and pricing behavior of other dealers, a dealer can also obtain information about the future direction of bond prices. The private information held by bond dealers will be reflected in their interdealer order flow and gradually become impounded into bond prices through the mechanisms described in Bayesian learning models.[9]

4.2 The expectations hypothesis and the classical term structure model

The analysis in this paper is based on a simple term structure model based on the expectations hypothesis. The classical expectations hypothesis constitutes the foundation of the vast literature on interest rate predictability, and implies that forward rates predict interest rate changes. Fama and Bliss (1987) and Campbell and Shiller (1991) find that forward rates have little predictive power for future interest rates and conclude that their results are inconsistent with the expectations theory. Instead they find that forward rates predict excess bond returns, a proxy for bond risk premia. Cochrane and Piazzesi (2005) confirm earlier findings by documenting that a linear combination of forward rates have strong forecasting power for all bond excess returns.

This section briefly reviews the expectations hypothesis employed in Fama and Bliss (1987) and Cochrane and Piazzesi (2005). The relationship between the price and the yield of a zero-coupon bond is shown in the following,

$$P^{(N)} = [1 + Y^{(N)}]^{-N}, \tag{1}$$

where $P^{(N)}$ is the price on a zero-coupon bond with N years to maturity and $Y^{(N)}$ is the yield to maturity of a zero-coupon bond with N years to maturity. Equation (1) shows that there is a one-to-one relationship between the price and the yield of a zero-coupon bond. An increase in the price leads to a decline in the yield to maturity and vice versa. By taking logs on both sides of equation (1) and expressing the yield as a function of price, equation (1) becomes

$$y^{(N)} = -\frac{1}{N}p^{(N)}, \tag{2}$$

where $y^{(N)}$ is the log yield and $p^{(N)}$ is the log price of a zero coupon bond with N years

[9] See for example O'Hara (1995).

to maturity. The return of a zero-coupon bond is

$$r_{t+1}^{(N)} = p_{t+1}^{(N-1)} - p_t^{(N)}, \tag{3}$$

where $r_{t+1}^{(N)}$ is the one period log return of a bond with N years to maturity at time t and N-1 years to maturity at time t+1. The expectations hypothesis of the term structure of interest rates can be stated in three different ways according to Cochrane (2001). He emphasizes that the hypothesis is "three equal statements about the pattern of (zero) yields across maturity". First, the expectations hypothesis states that bond yields are expected values of average future short term rates as shown in the following,

$$y_t^{(N)} = \frac{1}{N} E_t(y_t^{(1)} + y_{t+1}^{(1)} + y_{t+2}^{(1)} ... y_{t+N-1}^{(1)}) + Risk\ Premium. \tag{4}$$

Equation (4) says that the log yield of a zero-coupon bond is the average one-period yields over the life of the bond plus a risk premium. Second, the hypothesis implies that forward rates equals expected future spot rates,

$$f_t^{(N \to N+1)} = E_t(y_{t+N}^{(1)}) + Risk\ Premium, \tag{5}$$

where $f_t^{(N \to N+1)}$ is the forward rate quoted at time t for the one period interest rate from period N to period N+1, and $E_t(y_{t+N}^{(1)})$ is the time t expected one period spot rate at time t+N. In the classical term structure model, the risk premium is assumed to be zero or constant. Third, the expectation hypothesis implies that the expected holding period return is the same for bonds of all maturities,

$$E_t(r_{t+1}^{(N)}) = y_t^{(1)} + Risk\ Premium, \tag{6}$$

where $E_t(r_{t+1}^{(N)})$ is the one-period return at time t+1 expected at time t. The risk premium is also here zero or constant under the expectation hypothesis. By rearranging equation (6) it appears that the theoretical risk premium equals the expected excess return

$$E_t(exr_{t+1}^N) = E_t(r_{t+1}^{(N)}) - y_t^{(1)}, \tag{7}$$

where $E_t(exr^N_{t+1})$ is the excess return of a zero-coupon bond at time t+1 expected at time t. Equation (7) shows that the expected excess return is the expected return minus the one-period return expressed as the one-period zero yield.

4.3 Adapting the framework to short horizon forecasts

Whereas Fama and Bliss (1987) and Cochrane and Piazzesi (2005) analyze forecasting horizons of one to four years, this paper focuses on much shorter horizons. Two forecasting horizons are analyzed, one day and twenty days. The twenty day horizon is referred to as the monthly horizon. The paper predicts daily and monthly yield changes and excess returns on six zero coupon bonds with 1, 2, 3, 4, 5 and 10 years to maturity. Since the forecasting horizons are short relative to the maturity of the bonds, the yield changes and excess returns are estimated under the assumption that the remaining time to maturity of the bond is approximately the same at the beginning and at the end of the forecasting period. It is thus assumed that $N\ years - 1\ day \approx N\ years$ and $N\ years - 1\ month \approx N\ years$. Yield changes and bond returns are calculated according to

$$dy_{t+1}^{(N\ years)} = y_{t+1}^{(N\ years)} - y_t^{(N\ years)}, \tag{8}$$

and

$$r_{t+1}^{(N\ years)} = p_{t+1}^{(N\ years)} - p_t^{(N\ years)}, \tag{9}$$

where $dy_{t+1}^{(N\ years)}$ is the one-period change in the log yield of a N year zero-coupon bond. Equations (6) and (7) show that the expected excess return is a measure of the risk premium. Since expectations are unobservable, the actual excess return is used as a proxy for the bond risk premium,

$$exr_{t+1}^{(N\ years)} = r_{t+1}^{(N\ years)} - y_t^{(1m)} . \tag{10}$$

Equation (10) states that the actual excess bond return at time t+1 is the one-period bond return minus the one-period riskfree rate at time t. The one month zero rate, $y_t^{(1m)}$, is used as a proxy for the one-period riskless return.

Numerous studies, including Fama and Bliss (1987) and Cochrane and Piazzesi (2005), document that the bond risk premium is neither zero nor a constant, but time-varying. Therefore, changes in yields can, according to equation (4), be a result of either changes in expected future short rates or changes in the risk premium. Fama and Bliss (1987) find that the forward spread tracks changes in risk premia. The forward spread is defined as

$$FS_t^N \equiv f_t^{(N \rightarrow N+1)} - y_t^{(1)}, \tag{11}$$

where FS_t^N is the forward spread. Equation (11) states that the forward spread is measured as the one period forward rate starting at time N minus today's one period rate. The forward spread can also be stated as

$$FS_t^N = E_t(exr_{t+1}^N) + E_t(y_{t+1}^{(N)} - y_t^{(N)}), \tag{12}$$

which shows that the forward spread is the sum of the expected excess return and the expected one-period yield change. Fama and Bliss (1987) find that the forward spread is a poor predictor of interest rate changes, but that the forecast power increases somewhat with the horizon. Since forward rates are poor forecasters of interest rates, they conclude that yields are close to random walks. Equation (12) then suggests that the forward spread should predict the risk premium.

4.4 Daily and monthly forecasting models

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. One model, c), is based on lagged order flow only. The last two models, d) and e), include order flow in the two term structure models. Both the Fama-Bliss maturity dependent forward spread defined in equation (11) and forward rates are used as predictor variables.[10] However, in order to reduce the number of predictive variables, the three first principal components of forward rates are employed. 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 maturity dependent

[10] All models are also run with excess bond return as the left hand side variable, instead of yield changes, since there is a one-to-one relationship between a bond's yield and its price.

forward spread as the only predictor variable,

$$dy_{t+1}^{(N\ years)} = \beta_0 + \beta_1 FS_t^N + \varepsilon_{t+1}, \tag{13}$$

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,

$$dy_{t+1}^{(N\ years)} = \beta_0 + \beta_2^1 F_t^1 + \beta_2^2 F_t^2 + \beta_2^3 F_t^3 + \varepsilon_{t+1}, \tag{14}$$

where 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. 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,

$$dy_{t+1}^{(N\ years)} = \beta_0 + \beta_3^S OF_t^S + \beta_3^M OF_t^M + \beta_3^L OF_t^L + \varepsilon_{t+1}, \tag{15}$$

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,

$$dy_{t+1}^{(N\ years)} = \beta_0 + \beta_1 FS_t + \beta_3^S OF_t^S + \beta_3^M OF_t^M + \beta_3^L OF_t^L + \varepsilon_{t+1}, \tag{16}$$

$$dy_{t+1}^{(N\ years)} = \beta_0 + \beta_2^1 F_t^1 + \beta_2^2 F_t^2 + \beta_2^3 F_t^3 + \beta_3^S OF_t^S + \beta_3^M OF_t^M + \beta_3^L OF_t^L + \varepsilon_{t+1}. \tag{17}$$

Model d), presented in equation (16), includes the forward spread and order flow as predictive variables. Model e), presented in equation (17), includes the first three principal components of forward rates and the three order flow groups.

As the term structure literature finds that forward rates can predict bond excess returns, the predictive power of order flow on excess returns is also investigated. All regression models, presented in equations (13) to (17), are first applied to yield changes and then to bond excess returns. Each model is thus used twice for each maturity on the daily forecast horizon.

The models used at the monthly horizon are identical to the models used at the daily horizon, except that t indicates month instead of day. In order to avoid any bias due to overlapping observations, the monthly analysis is based on 75 non-overlapping monthly observations.[11] 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 in equations (13) to (17) are thus also used for the monthly predictions of yield changes and excess returns.

5 In-sample results based on aggregate order flow

This section discusses the in-sample results based on the five models presented in the previous section. Forecasts of yield changes and excess returns are based on aggregate interdealer order flow and traditional term structure variables as predictive variables. Section 5.1 presents the results for daily yield changes and daily excess returns. Section 5.2 presents the results for monthly yield changes and monthly excess returns.

5.1 Daily predictions

Table 7 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 (13) to (17). 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

[11] Recent studies have shown that long horizon forecasts based on overlapping observations of highly persistent variables may lead to spurious results. Boudoukh, Richardson and Whitelaw (2006) show that under the null hypothesis of no predictability, many persistent variables produce coefficient estimates and R^2 's that are highly correlated across horizons. In order to avoid a possible bias due to the high persistence of monthly order flow based on overlapping observations, this study uses non-overlapping monthly observations.

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 116 basis 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 7 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 when including the forward spread in the model. 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.

Table 8 presents the results of the in-sample predictions of daily bond excess returns, based on the same five models as above. The table reveals that while forward rates have little predictive power for yield changes, they have significant forecasting power for bond excess returns. The results from model a) indicate that the forward spread has some predictive power for excess returns, and the coefficients are significant at the 10 percent level or better across all yields. Model b) shows that principal components of forward rates have some predictive power for excess returns, especially at the short end of the yield curve. The coefficients of the first and second principal components are statistically significant for excess returns for 1-3 year bonds and the adjusted R^2s vary from 5.3 to 0.4 percent. For 4 and 5 year excess returns, the two first components are no longer significant, but the third principal component is significant. For the 10-year daily excess return both the second and third principal components have significant forecasting power. These results are in accordance with Fama and Bliss (1987) and Cochrane and Piazzesi (2005) who find that forward rates can predict excess returns, but not interest rates.

Model c) shows that short, medium and long term order flow can predict excess returns also. The predictive power of order flow on excess returns and yield changes is of similar magnitude with R^2s varying from 3.0 to 1.1 percent. In line with the results for yield changes, medium term order flow has strongest predictive power both economically and statistically. The sign, however, is opposite that of yield changes, due to the inverse relationship between the price and yield of a bond shown in equation (1).

Models d) and e) which include both forward rates and order flow as predictive variables, outperform the first three models in predicting bond excess returns. The adjusted R^2s of model e) vary between 7.8 and 1.3 percent. In all, the results at the daily horizon show that the predictive power of order flow is significant in the presence forward rates. This suggests that forward rates and order flow have independent predictive power for bond excess returns and thus confirm the findings for daily yield changes.

5.2 Monthly predictions

Table 9 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.[12] 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

[12] 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.

predictive power of lagged order flow increases with the horizon when looking at exchange 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 71 basis 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.

Table 3.10 presents the in-sample predictions for monthly excess returns. The results of model a) and model b) which includes forward rates only, reveal that the predictive power of forward rates on bond excess returns increases from the daily to the monthly horizon. Also, the predictive power of forward rates is considerably higher at the short end of the yield curve than at the long end with an adjusted R^2 for model b) of 41.1 percent for 1-year excess returns and 0.5 percent for 10-year excess returns. In line with the results for monthly yield changes, it is short and medium term monthly order flow which predicts excess returns. The results further show that lagged order flow predicts the variation in monthly yield changes and monthly excess returns of similar order of magnitude. The information in monthly order flow may thus be related to business cycle variations.

The results so far can be summarized in five main points. First, order flow can predict daily and monthly yield changes and excess returns across all maturities. Second, order flow has predictive power in the presence of the forward spread and the first three principal components of forward rates. Third, the explanatory power of order flow is strongest at the short end of the yield curve. Fourth, medium term order flow, including trades in bonds with 4 to 7 years to maturity, has the strongest predictive power. Fifth, forward rates have little predictive power for yield changes, but some predictive power for excess returns, especially at the monthly horizon. These findings document that interdealer order flow contains information over and above the information contained in the current yield curve.

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

In order to determine whether a model is useful for forecasting purposes, its out-of-sample performance should be tested. Goyal and Welch (2008) emphasize the importance of testing a model's out-of-sample performance as they find that many predictive variables are unstable over time. This section evaluates out-of-sample forecasts based on the models discussed in the previous section. However, if a model has no predictive power in-sample, there is no reason to test the model out-of-sample using the same data set. Consequently only models and variables which have predictive power in-sample are included. First, the pure order flow model is tested. Second, if significant in-sample, the forward rate model is tested.

In order to evaluate the out-of-sample performance of order flow and forward rates, the method in Goyal and Welch (2008) is employed. Each model is compared to a benchmark model. The benchmark model is a version of the random walk hypothesis, and uses the historic average as the prediction for the next period. Goyal and Welch (2008) find some evidence that variables that can predict in-sample cannot predict out-of-sample better than the historic average, implying that this is a suitable benchmark. The random walk model (RW) can be written as

$$dy_{t+1}^{(N\ years)} = c + \upsilon_{t+1}, \tag{18}$$

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 (18) states that the RW forecast depends on the historic average of yield changes up to period t. To compare the out-of-sample performance of the order flow 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. McCracken (2007) has developed a test statistic which 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

$$MSE - F = (T - h + 1) * (\frac{MSE_R - MSE_U}{MSE_U}), \tag{19}$$

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 (19) defines the test statistic as the 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.[13] 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 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

Tables 11 and 12 display the results of the out-of-sample predictions of yield changes and excess returns at the daily frequency. The recursive forecasts cover the period from September 2000 to September 2005. The tables compare the out-of-sample predictive power

[13] 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.

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. Table 11 shows the models predicting daily yield changes. The first column 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.

Table 11 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 some order flow variables were significant in the in-sample predictions. Only order flow variables are thus included in the out-of-sample predictions. 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 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 simple term structure model is only tested for the 10-year yield as the in-sample predictions found significant forward rate factors for 10 year yield changes only. The MSE-F statistic is significant, but much smaller than for the order flow model. Also the MSE ratio of 1.00 for the forward rate model and a MSE ratio of 0.99 for the order flow model indicate that the order flow model outperforms both the term structure model and the RW.

Table 12 compares the predictions of daily bond excess returns. Both the order flow model and the simple term structure model are included as alternative models, and the order flow model outperforms the RW for all maturities. The MSE-ratios vary from 0.97 to 0.99 and the MSE-F test statistic is significant at the 1 percent level for all maturities. The results confirm that lagged order flow models significantly outperform the random walk in predicting next day bond excess returns along the whole yield curve. In line with earlier studies, the simple term structure model has out-of-sample forecasting power for excess returns. The MSE-ratios vary from 0.95 to 1.01 and the MSE-F test statistic is significant at the 5 percent level for all maturities, except for the 3-year excess return. The forward rate model thus outperforms the RW for most maturities. However, for all maturities, except for 1-year excess returns, the order flow model produces better predictions than both the forward rate model and the RW model. When comparing the MSE-ratios and values of the test statistics in Table 12 to those in Table 11, order flow appears to have roughly the same forecasting power for yield changes and excess returns.

6.2 Monthly predictions

Table 13 and 14 present the results of monthly predictions of yield changes and excess returns based on non-overlapping data. The recursive forecasts cover the period from August 2001 to September 2005. The tables compare 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.

Table 13 shows that the order flow model clearly outperforms the RW in predicting monthly yield changes along the whole yield curve. The simple 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 - 1.0.

Figure 2 illustrates the performance of the order flow 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. Figure 3 shows the difference in accumulated prediction errors between the forward rate model and the random walk. The curve, which is negative in 2002, indicates that the simple term structure model in some periods performs worse than the RW model. Table 14, presenting the results for monthly excess returns, shows that the out-of-sample predictions for excess returns are in line with the results for monthly yield changes.

The main finding in this section is that the out-of-sample results confirm the in-sample results, indicating that lagged order flow is a robust predictor of yield changes and excess returns. Order flow has predictive power along the whole yield curve, but predictability is strongest at the short end of the yield curve. For excess bond returns, both order flow and forward rates have predictive power. Order flow has roughly the same predictive power for yield changes and excess returns, indicating that order flow contains information on risk premia that is additional to the information contained in forward rates.

7 The source of predictability - trade type

The results from the previous section show that interdealer order flow has predictive power for yield changes and bond excess returns on both daily and monthly horizons. This section seeks to investigate the source of the predictive power in interdealer order flow. Two possible sources will be discussed. The first source is private information held by dealers due to their trades with informed customers.[14] The second source is private information held by dealers due to their skill in collecting and processing relevant information. In order to investigate whether the source of predictability is customer trades or dealer skill, a proxy for informed customer trades is included in the analysis. If order flow based on informed customer trades predict yield changes, we infer that private information from informed customers is an important source of predictability. If interdealer order flow unrelated to informed customer order flow predict yield changes, we infer that dealer skill is a source of predictability.

[14] It is assumed that dealers take advantage of informed customer trades by doing interdealer trades in the same direction. If an informed customer buys bonds from dealer A, dealer A will infer that bonds are undervalued and she will initiate a buy trade from dealer B. Interdealer order flow will thus reflect informed customer trades.

7.1 Delayed publication customer trades

As a proxy for informed customer order flow, order flow based on delayed publication customer trades is employed. As mentioned in section 3.1, bond dealers have the possibility to delay the publication of a trade until the end of the day. A dealer will most likely use this possibility when she believes a trade contains information she can benefit from by hiding it from the other dealers. By delaying the publication of the trade, she can trade on the information before it is available to other dealers. This paper assumes that customer trades entered as delayed publication trades are trades by informed customers.

The information in interdealer order flow orthogonal to informed customer order flow is assumed to contain private information acquired by dealer skill. To derive the part of interdealer order flow orthogonal to informed customer trades, the following regression is employed;

$$OF_t = c + \psi HCOF_t + \upsilon_t, \tag{20}$$

where OF_t is interdealer order flow and $HCOF_t$ is the order flow based on delayed publication customer trades. The residuals from the regression presented in equation (20), υ_t, are subsequently renamed,

$$\upsilon_t = resOF_t, \tag{21}$$

where $resOF_t$ is residual interdealer order flow, or the part of interdealer order flow orthogonal to informed customer trades. Residual order flow is derived separately for short, medium and long term order flow based on delayed publication customer trades for the same three maturities. To test for the source of predictability in interdealer order flow, the following three models are run for each maturity,

$$dy_{t+1}^{(Nyears)} = \gamma_0 + \mathbf{\Lambda F}_t + \gamma_4 HCOF_t^S + \gamma_5 HCOF_t^M + \gamma_6 HCOF^L + \varepsilon_{t+1}, \tag{22}$$

$$dy_{t+1}^{(Nyears)} = \varphi_0 + \mathbf{\Lambda F}_t + \varphi_4 resOF_t^S + \varphi_5 resOF_t^M + \varphi_6 resOF_t^L + \upsilon_{t+1}, \tag{23}$$

$$dy_{t+1}^{(Nyears)} = \beta_0 + \mathbf{\Lambda F}_t + \sum_{i=S}^{L} \gamma_i HCOF_t^i + \sum_{i=S}^{L} \varphi_i resOF_t^i + \epsilon_{t+1}, \tag{24}$$

where $i = S, M, L$ indicates short term, medium term and long term maturity respectively.

The model presented in equation (22) tests the predictive power of informed customer trades. This model is called model k) for both daily forecasts and monthly forecasts. In addition to delayed publication customer order flow with short, medium and long term maturity, $HCOF_t^S$, $HCOF_t^M$ and $HCOF_t^L$, the model also includes the three first principal components of forward rates, $\mathbf{F}_t$ ($F1_t$, $F2_t$ and $F3_t$), and a constant. The model presented in equation (23) tests the predictive power of order flow reflecting dealer skill. It is called model l) for both daily forecasts and monthly forecasts. In addition to interdealer order flow orthogonal to informed customer order flow, $resOF_t^S$, $resOF_t^M$ and $resOF_t^L$, the model also includes the three principal components of forward rates, and a constant. The model shown in equation (24) includes both the proxy for informed customer trades and the part of interdealer order flow reflecting dealer skill, as well as forward rates. This model is referred to as model m) for both daily forecasts and monthly forecasts.

7.2 Results

This section presents the results for daily and monthly forecasts of yield changes and excess returns based on the three models described above. Table 15 displays the results for daily yield changes. The predictive power of interdealer order flow orthogonal to informed customer trades is higher than the predictive power of informed customer trades for yield changes along the whole yield curve, indicating that dealer skill and effort is an important source of predictability. However, model m) has higher explanatory power than model l), indicating that customer trades also is a source of predictability, but less important than dealer skill and effort, at the daily horizon. Table 16 displays the results for predictions of daily excess returns. The results are in line with the results for daily yield changes.

Table 17 presents the in-sample predictions of monthly yield changes. At the monthly horizon, the predictive power of interdealer order flow orthogonal to informed customer trades is higher than the predictive power of informed customer trades for 1-5 year yield changes. However, for 10 year yield changes only long term informed customer order flow has significant predictive power. Table 18 shows the in-sample predictions of monthly bond excess returns. The results are similar to the results for monthly yield changes with the same predictor variables being significant for the different maturities.

The in-sample results thus indicate that dealer skill and effort is the most important source of predictability for both yield changes and excess returns for maturities of 1 - 5 years. However, at the long end of the yield curve, informed customer trades appear to be the main source of predictability, especially at the monthly horizon.

Table 19 and 20 present the results for daily out-of-sample forecasts of yield changes and excess returns based on the first two models of the previous section. As in the out-of-sample analysis in section 6, only significant in-sample variables are included. First, predictions based on order flow reflecting informed customer trades, $HCOF$, are compared to the random walk. Then predictions based on order flow reflecting trades based on dealer skill, $resOF$, are compared to the random walk.

Table 19 shows that interdealer order flow orthogonal to informed customer trades has highly significant out-of-sample forecasting power for yield changes along the whole yield curve. The proxy for informed customer trades has little predictive power out-of-sample. The MSE-F test statistic for informed customer order flow is only significant at the 10 percent level except for 10 year yield changes where it is significant at the 5 percent level. The table further shows that the ratio of the mean squared errors (MSE) is smaller for the orthogonal interdealer order flow model than for the informed customer order flow model indicating that dealer skill and effort are the main source of out-of-sample predictability. Table 20 shows that the results of the out-of-sample predictions of daily excess returns are in line with the results in Table 19. Based on the out-of-sample results of the two alternative models for daily yield changes and excess returns, it appears that while the orthogonal interdealer order flow model clearly outperforms the other models, the forecasts based on informed customer order flow are only slightly better than the random walk model.

Table 21 and 22 display the results of the out-of-sample predictions of monthly changes in yields and excess returns, based on the same models as above. Interdealer order flow orthogonal to informed customer trades has significant out-of-sample predictive power for yield changes up to 5 years at the monthly horizon. The model including the proxy for informed customer order flow cannot outperform the random walk. This is a somewhat surprising result given the in-sample significance of long term informed customer order flow at the monthly horizon. By looking at a graph displaying the metric used by Goyal and Welch (2008) the in-sample predictive power of this variable appears to be due to a few instances of high predictability and poor predictability the rest of the time.[15] For the 10 year bond none of the alternative models can beat the RW. Table 22 confirms that the results for excess returns are in line with the findings for monthly yield changes.

In all, the results in this section show that the model based on interdealer order flow orthogonal to informed customer trades outperforms the other models both in-sample and out-of-sample for maturities up to 5 years. The proxy for informed customer order flow has no out-of-sample predictive power except for daily changes in the 10 year yield. This suggests that private information due to dealer skill could be an important source of predictability in interdealer order flow.

8 The source of predictability - individual dealers

Whereas the previous section investigates the source of predictability according to trade type, this section explores the source of predictability according to individual dealer differences. The new data set used in this study gives an insight into dealer behavior not conveyed by other data sets. By applying individual dealer identities, the transactions data are separated into customer trades and interdealer trades for each dealer. In order to investigate whether the main source of predictive power is private information obtained from customer trades or from dealer skill and effort, individual dealers are characterized according to different criteria. These criteria include dealer size, customer base and interdealer activity. Also the number of active (initiated) interdealer trades and passive (initiated by others) interdealer trades as a share of the total number of trades are measured for each dealer. If the interdealer order flow of dealers with a large customer base has higher predictive power than the order flow of dealers with a small customer base, information from customer trades may be an important source of predictability. If the order flow of dealers with a high share of active interdealer trades relative to passive interdealer trades has higher predictive power than the order flow of dealers with a low share, private information gained from dealer skill and effort could be an important source of predictability.

[15] The graph is not included in the paper, but is available upon request.

8.1 Dealer characteristics

Seven dealers, representing about 85 percent of the trades in the data set, are included in this part of the analysis.[16] 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. The dealers are characterized by size, their customer base, interdealer activity and relative share of active interdealer trades to passive interdealer trades. Size is measured as a dealer's total market share in the customer market and the interdealer market combined. The customer base is measured as a dealer's market share in the customer market. Interdealer activity is measured as the value of a dealer's active interdealer trades relative to the value of her customer trades. This ratio may indicate whether a dealer possesses private information. 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.[17] A dealer who is impatient is likely to possess private information.[18] She wants to initiate trades because she wants to utilize this information before other dealers learn about it. A high share of initiated interdealer trades may thus indicate that a dealer uses skill in acquiring and processing information. Conversely, a low share of initiated interdealer trades may indicate that a dealer does not have this skill.

Table 23 and Table 24 present the characteristics of the seven dealers. Table 23 is based on the value of trades in NOK while Table 24 is based on the number of trades. In Table 23 the dealers are listed according to size in column 1. The total market share of each dealer is displayed in the second column. There are four large dealers, with market shares ranging from 17 to 24 percent, constituting 85 percent of the market. The remaining three dealers are small constituting the remaining 15 percent of the market. 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,

[16] The order flow of dealers who were 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.

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

[18] This is in line with the findings of Osler (2008) in the foreign Exchange market.

especially Dealer 1 and Dealer 2 with a market share of around 25 percent each.

The fourth column of Table 23 displays interdealer activity, which can be a measure of dealer skill. This measure varies substantially between dealers. Among the four large dealers it varies between 19 and 42 percent.[19] If dealer skill in acquiring private information is an important source of predictability, one would expect dealers with a high ratio to predict better than dealers with a low ratio. One of the large dealers, Dealer 2, differs substantially from the others by displaying low interdealer activity. This indicates that Dealer 2 is a passive dealer.

In Table 24 the total number of trades entered into by each dealer are divided into interdealer trades and customer trades. Interdealer trades are then 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 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. The share of active interdealer trades relative to the share of passive interdealer trades gives an indication of how active the dealers is. If active dealers have predictive ability their skill in acquiring private information may be an important source of predictability.

In order to investigate the predictive power of the seven dealers, the predictability of the individual interdealer order flow of each dealer is tested by employing the following equation for each yield maturity at the daily and monthly horizon,

$$dy_{t+1}^{(N\ years)} = \beta_0 + \mathbf{\Lambda F}_t + \beta_3 OF_{D^i,t}^S + \beta_4^s OF_{D^i,t}^M + \beta_5^s OF_{D^i,t}^L + \varepsilon_{t+1}, \tag{25}$$

where $i = 1, 2, 3, 4, 5, 6, 7$ identifies the seven dealers, β_0 is a constant, $\mathbf{F}_t$ is a vector including the first three principal components of forward rates and $OF_{D^i,t}^S$, $OF_{D^i,t}^M$ and $OF_{D^i,t}^L$ are the short term, medium term and long term interdealer order flow of dealer i. Based on the results of the in-sample predictions of the model presented in equation (25),

[19] 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.

out-of-sample predictions are made for dealers and variables with significant in-sample predictive power.

8.2 Results

The results for each dealer are displayed in Table 25 to Table 30. In order to preserve space, forecasts of bond excess returns are not included in this part of the analysis as the results in the previous sections show that they are similar to those for yield changes. Tables 25 and 26 display the results for daily yield changes. Table 25 includes 1 to 3 year yield changes and Table 26 includes 4 to 10 year yield changes. The predictive regressions for each dealer include individual dealer order flow of the three maturity groups as well as a constant and the three first principal components of forward rates. The results show that the predictive power varies substantially between dealers, also between dealers of equal size. Dealer 1 is the best predictor. The predictive power of Dealer 1, which is mainly due to short and medium term order flow, varies between 2.3 and 1.0 percent at the daily horizon. The long term order flow of Dealer 1 has significant forecasting power for 10 year bonds only. Dealer 4, which is a large dealer with a large customer base, is the second best predictor. The predictive power of Dealer 4 is due to long term order flow. The R^2s for the different maturities vary between 0.6 and 1.4 percent at the daily horizon. Also, the medium term order flow of Dealer 5, which is a medium size dealer, has predictive power for 1 to 4 year yield changes. Table 24 shows that Dealer 5 has a much higher share of active interdealer trades than passive interdealer trades. This indicates that Dealer 5 is informed and initiates trades to benefit from her information. The order flows of Dealer 2, Dealer 3, Dealer 6 and Dealer 7 have no predictive ability at the daily horizon, except for 10-year yield changes where the R^2s vary between 0.5 and 0.9 percent. Dealer 2 is a large dealer with little interdealer activity and a low share of active interdealer trades. Dealer 3 is a large dealer with large interdealer activity. Dealer 6 is a small dealer with a slightly smaller share of active than passive interdealer trades. Dealer 7 is a very small dealer with very high interdealer activity and a high share of initiated interdealer trades. These results indicate that dealers possess heterogeneous private information at the daily horizon.

Tables 27 and 28 display the results for monthly yield changes. Table 27 include 1 to 3 year yield changes and Table 28 include 4 to 10 year yield changes. The predictive regressions for each dealer include monthly individual dealer order flow of the three maturity groups as well as a constant and the three first principal components of monthly forward rates. The predictive power varies substantially between dealers, and Dealer 1 appears to be the best predictor also at the monthly horizon. The predictive power of Dealer 1 order flow at the monthly horizon vary from 11.9 to 4.7 percent measured by R^2 for 1 to 10 year yield changes. Dealer 3 is the second best predictor at the monthly horizon. The short and medium term order flow of Dealer 3 predicts 1 to 5 year monthly yield changes, but not 10 year yield changes. Dealer 4 is the best predictor of 10-year yield changes. A one standard deviation increase in the short term order flow of Dealer 4 leads to a fall in the 10-year yield of 1,2 basis points the next month. The other dealers have little predictive power at the monthly horizon. The medium term order flow of Dealer 6 is significant for all maturities, but the R^2s are close to zero. It is important to note that the third forward rate factor has predictive power for 2 to 5 year yields at the monthly horizon. The results at the monthly horizon indicate that dealers have heterogeneous private information at the monthly horizon as well.

Table 29 and Table 30 display the out-of-sample results at the daily and monthly horizon, respectively. As in the previous sections, only variables that are significant in-sample are included. Table 29 reveals that the lagged order flow of Dealer 1 has the strongest out-of-sample predictive power for all maturities, except for the 10 year yield. The MSE ratios are all well below 1 and the MSE-F test statistic is significant at the 1 percent level for all maturities. This clearly indicate that the Dealer 1 order flow model outperforms the RW. The interdealer order flow of Dealer 4 and Dealer 5 also have significant out-of-sample predictive power for 1 to 5 year maturities, but the MSE ratios are greater than that of Dealer 1. For 10 year yields the order flow of Dealer 4 produces the best out-of-sample predictions. Dealer 2, Dealer 3, Dealer 6 and Dealer 7 have no out-of-sample predictive power at the daily horizon.

Figure 3.4 compares the predictive power of the order flows of Dealer 1 and Dealer 2 for daily 3 year yield changes. It displays the Goyal and Welch (2008) metric for comparing the out-of-sample predictive power of the order flow model to the RW for the two dealers. An increase in the metric illustrates that the order flow model performs better, while a fall in the metric illustrates that the RW performs better. The metric for Dealer 1 displays an upward sloping curve over the period as a whole. This means that the model based on Dealer 1 order flow outperforms the RW. The metric for Dealer 2 displays an initial fall and then remains constant for the rest of the period. This indicates that the model based on Dealer 2 order flow is outperformed by the RW. The figure clearly illustrates that while the order flow of Dealer 1 has predictive power, the order flow of Dealer 2 has not.

Table 30 shows out-of-sample results at the monthly horizon. The medium term order flow of Dealer 1 gives the best predictions for monthly yield changes. The MSE ratios of this model are around 0.9 and the MSE-F test statistics are significant at the 1 percent level. Dealer 3, who has no predictive power at the daily horizon, has out-of-sample predictive power for 1 to 4 year yield changes when employing short and medium term monthly order flow. Finally, the short term order flow of Dealer 4 has significant out-of-sample predictive power along the whole yield curve. The order flows of the other dealers have no predictive power at the monthly horizon. The exception is Dealer 5 who can forecast 1 to 3 year yield changes with short term order flow. Figure 5 shows that the monthly order flow of Dealer 1 clearly outperforms the RW for monthly 3-year yield changes while the order flow of Dealer 2 does not.

The results in this section document that only two out of seven dealers have significant forecasting ability for all yield changes at both horizons. These dealers are Dealer 1 and Dealer 4. They are large dealers with a total market share of 24 and 17 percent and customer market share of 24 and 18 percent, respectively. They have an interdealer activity, measured as the value of their active interdealer trades relative to their customer trades, close to average. The share of active interdealer trades is higher than the share of passive interdealer trades for Dealer 1 and the shares are about equal for Dealer 4.

Two dealers have some forecasting ability. The order flows of these dealers predict yield changes from parts of the yield curve or on only one horizon. Dealer 3 has predictive power for 1 to 4 year yield changes at the monthly horizon only. Dealer 3 has a total market share of 21 percent and a customer market share of 19 percent. She has an interdealer activity above average and has a slightly higher share of active than passive interdealer trades, indicating that this dealer is active. Dealer 5 has predictive power for 1 to 5 year yield changes at the daily horizon and 1 to 3 year yield changes at the monthly horizon.

Dealer 5 appears to be an active dealer with a total market share of 9 percent and a customer market share of 9 percent, an effort above average and a substantially higher share of active than passive interdealer trades.

Three dealers, one large and two small, have no forecasting ability. The large dealer, Dealer 2, has a total market share of 23 percent and has little interdealer activity, with a share of initiated interdealer trades relative to customer trades of 19 percent. The share of active interdealer trades is much lower than the share of passive interdealer trades, indicating that Dealer 2 is a passive dealer. Table 23 shows that Dealer 1 and Dealer 2 have the same amount of customer trades, with a market share in the customer market of 24 and 25 percent respectively. Given that the order flow of Dealer 1 has significant predictive power for future yield changes and the order flow of Dealer 2 has no predictive power, the main source of predictability in interdealer order flow does not appear to be customer trades. Table 23 indicates that their interdealer activity differs and Table 3.24 shows that Dealer 1 has a majority of active trades in the interdealer market while Dealer 2 has a majority of passive trades. Dealer 1 appears to possess private information which she is trading on in the interdealer market. Dealer 2 appears to be uninformed and thus a passive dealer in the interdealer market. This indicates that dealer skill and effort is an important source of predictability in interdealer order flow.

Other factors, for example customer types, may also influence the predictability of individual interdealer order flow. If the customer groups of the different dealers are heterogeneous, this may explain part of the differences between dealers. The information in customer trades could depend on the type of customer, and not the size of the customer base alone. A hedge fund manager is for example likely to be better informed than an investment officer in the pension fund of a domestic firm. Osler and Vandrovych (2009) find that customers in foreign exchanges markets are heterogeneous and that hedge funds provide private information while non-financial corporations and mutual funds do not. This could also be the case in fixed income markets. However, a dealer's skill in identifying her informed customers can also explain the predictability of her interdealer order flow.

The results in this section indicate that there is an important source of predictability in interdealer order flow independent of customer trades that could be related to dealer skill in collecting and interpreting relevant information. In all, the findings in this and the previous section indicate that dealers with predictive power possess private information unexplained by the size of their customer base. The forecasting ability of individual dealers appears to be related to whether dealers are active or passive in the interdealer market. Active dealers are more likely to possess private information than passive dealers. Thus, dealer skill in acquiring and interpreting public and private information relevant for future bond prices could explain why the order flows of some dealers are better predictors of future yield changes than the order flows of others.

9 Conclusion

The main contribution of this paper is to include bond market order flow as a predictive variable in a traditional term structure model. Whereas term structure models only include variables that are based on the current yield curve, like forward rates, yield spreads and common yield factors, order flow potentially contains information that is not yet incorporated into the yield curve. According to the market microstructure literature the process of price formation in financial markets, in which asset prices adjust to full information prices, do not occur instantaneously, but evolves in markets over time through trading activity. Order flow will thus gradually convey private information held by market participants. Private information in bond markets can include interpretations of macroeconomic indicators and thus heterogeneous expectations on the future monetary policy rate as well as information on supply side and demand side shocks influencing market liquidity. Recent studies indicate that information unrelated to the current term structure can predict bond prices. Ludvigson and Ng (2009) find predictable variation in bond returns related to macroeconomic factors independent of forward rates. The results in this paper are consistent with these studies by documenting that lagged bond market order flow has significant forecasting ability for yield changes beyond the predictive power of forward rates both at the daily horizon and the monthly horizon.

Another important contribution of this paper is to document that individual dealers are heterogeneous and that the predictive power of their order flows varies substantially. The source of predictability in interdealer order flow does not appear to be related to the size of the customer base of a dealer. When comparing two large dealers with the same size customer base, only the order flow of one dealer has predictive power. This dealer trades more in the interdealer market and has a higher share of initiated interdealer trades than the other dealer which is consistent with possession of information. This indicates that at least some dealers play an active role in the price formation process and that the source of predictability in their interdealer order flow is something other than the volume of customer trades; dealer skill. Dealers can acquire private information by using their skill in collecting and interpreting public information and in aggregating private information from trades with customers and other dealers. Whereas dealer skill can be related to the ability to discern informed customers from uninformed customers it can also be related to the ability to correctly infer yield changes based on interpretations of macroeconomic indicators and other publicly available information. Interdealer order flow can thus reflect macroeconomic information which is in line with the findings of Ludvigson and Ng (2009) and Andersen and Benzoni (2010).

The results in this paper further document that order flow predicts excess returns. Order flow has roughly the same predictive power for excess returns and yield changes when controlling for the effect of forward rates. This suggests that order flow predicts risk premia, but risk premia beyond, and perhaps different from, those predicted by forward rates.

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Table 1
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. The three first components explain 99,9 percent of the variation in forward rates.

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

Table 2
Loadings of principal components of forward rates

The table presents the loadings of the first three principal components extracted from six forward rates. These are the one month forward rates maturing in 1, 2, 3, 4, 5 and 10 years. 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 of Litterman and Scheinkman (1991).

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

Table 3
Descriptive statistics daily data

The table presents the descriptive statistics for daily yield changes, excess returns, order flow data, forward factors and forward spreads and includes the first order autocorrelation.

Series	obs	mean	std.err	minimum	maximum	AR(1)
dm1	1504	-0.003	0.070	-0.58	0.56	-0.152
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
exr1	1504	-0.0002	0.0004	–0.003	0.003	0.156
exr2	1504	-0.0002	0.0010	-0.006	0.009	0.138
exr3	1504	-0.0002	0.0015	-0.009	0.014	0.107
exr4	1504	-0.0002	0.0020	-0.012	0.017	0.087
exr5	1504	-0.0002	0.0024	-0.014	0.020	0.082
exr10	1504	-0.0001	0.0043	-0.020	0.023	0.095
OF^S	1504	-0.75	3.78	-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
HCOF^S	1504	-0.09	3.07	-18	13	0.105
HCOF^M	1504	0.17	2.37	-12	14	0.068
HCOF^L	1504	-0.19	2.72	-15	14	0.058
resOF^S	1504	0.00	3.75	-26	23	0.144
resOF^M	1504	0.00	3.67	-25	27	0.053
resOF^L	1504	0.00	4.39	-28	21	0.097
$F1$	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

Table 4
Descriptive statistics monthly data

The table presents the descriptive statistics for monthly yield changes, excess returns, order flow data, forward factors and forward spreads and includes the first order autocorrelation.

Series	obs	mean	std.err	minimum	maximum	AR(1)
dm1	75	-0.055	0.29	-1.13	0.53	0.157
dy1	75	-0.046	0.27	-0.98	0.47	0.382
dy2	75	-0.042	0.29	-0.80	0.56	0.244
dy3	75	-0.040	0.29	-0.69	0.64	0.173
dy4	75	-0.039	0.27	-0.68	0.67	0.151
dy5	75	-0.038	0.26	-0.63	0.67	0.154
dy10	75	-0.037	0.22	-0.53	0.61	0.153
exr1	75	-0.0035	0.0032	–0.0098	0.0064	0.577
exr2	75	-0.0031	0.0058	-0.0149	0.0123	0.309
exr3	75	-0.0028	0.0084	-0.0200	0.0156	0.209
exr4	75	-0.0025	0.0105	-0.0274	0.0214	0.178
exr5	75	-0.0021	0.0124	-0.0338	0.0255	0.177
exr10	75	-0.0004	0.0213	-0.0601	0.0463	0.169
OF^S	75	-14.93	28.45	-97	70	0.350
OF^M	75	-3.38	21.06	-77	44	0.308
$\mathrm{OF}L$	75	-25.36	28.02	-111	22	0.348
HCOF^S	75	-1.17	5.13	-19	13	0.534
HCOF^M	75	-0.44	5.03	-22	11	0.383
HCOF^L	75	-4.76	14.0	-63	21	0.543
resOF^S	75	0.00	27.67	-79	87	0.338
resOF^M	75	0.00	18.80	-60	47	0.168
resOF^L	75	0.00	26.76	-87	43	0.297
$F1$	75	-0.027	2.38	-4.93	3.76	0.932
$F2$	75	0.011	0.62	-1.19	1.24	0.826
$F3$	75	-0.008	0.20	-0.84	0.76	0.468
fwd spread1	75	0.041	0.73	-1.67	1.46	0.886
fwd spread2	75	0.256	1.15	-1.64	2.51	0.948
fwd spread3	75	0.473	1.45	-1.58	3.30	0.968
fwd spread4	75	0.625	1.62	-1.60	3.72	0.975
fwd spread5	75	0.719	1.71	-1.63	3.94	0.977
fwd spread10	75	0.847	1.79	-1.67	4.05	0.976

Table 5
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, informed customer order flow and interdealer order flow orthogonal to informed customer order flow.

	OF^S	OF^M	OF^L	HCOF^S	HCOF^M	HCOF^L	resOF^S	resOF^M	resOF^L
OF^S	1.000								
OF^M	0.241	1.000							
OF^L	0.190	0.235	1.000						
HCOF^S	0.083	0.012	-0.024	1.000					
HCOF^M	0.045	0.114	-0.032	0.129	1.000				
HCOF^L	-0.002	0.024	0.124	0.023	0.037	1.000			
resOF^S	0.997	0.241	0.193	-0.000	0.035	-0.004	1.000		
resOF^M	0.238	0.993	0.240	-0.002	0.000	0.020	0.239	1.000	
resOF^L	0.192	0.234	0.992	-0.027	-0.037	0.000	0.195	0.240	1.000
$F1$	-0.093	-0.006	-0.087	0.119	-0.045	-0.125	-0.104	-0.001	-0.072
$F2$	-0.033	-0.025	0.041	0.017	-0.020	0.019	-0.034	-0.023	0.039
$F3$	0.064	0.029	0.054	0.061	0.019	0.076	0.060	0.027	0.045

Table 6
Unconditional correlations monthly data

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

	OF^S	OF^M	OF^L	HCOF^S	HCOF^M	HCOF^L	resOF^S	resOF^M	resOF^L
OF^S	1.000								
OF^M	0.568	1.000							
OF^L	0.239	0.108	1.000						
HCOF^S	0.137	0.100	-0.109	1.000					
HCOF^M	0.129	0.073	-0.161	0.463	1.000				
HCOF^L	0.165	0.010	0.369	-0.022	0.173	1.000			
resOF^S	0.991	0.560	0.256	-0.000	0.067	0.170	1.000		
resOF^M	0.560	0.997	0.120	0.067	0.000	-0.003	0.556	1.000	
resOF^L	0.191	0.112	0.929	-0.108	-0.242	-0.000	0.208	0.130	1.000
$F1$	-0.272	-0.031	-0.287	0.242	-0.189	-0.415	-0.308	-0.017	-0.144
$F2$	-0.100	-0.137	0.192	0.080	-0.092	0.203	-0.112	-0.131	0.125
$F3$	0.125	0.125	0.006	0.084	0.203	0.019	0.115	0.111	-0.001

Table 7
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), 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	$\mathbf{0.58}^*$ (3.02)							0.008
	b		0.00 (0.53)	0.00 (1.51)	−0.01 (−0.64)				0.001
	c					$\mathbf{-0.09}^*$ (−2.05)	$\mathbf{-0.13}^*$ (−3.86)	−0.05 (−1.54)	0.029
	d	$\mathbf{0.54}^*$ (2.79)				$\mathbf{-0.08}$ (−1.78)	$\mathbf{-0.13}^*$ (−3.94)	$\mathbf{-0.06}$ (−1.86)	0.036
	e		0.00 (0.05)	0.00 (1.49)	−0.00 (−0.28)	$\mathbf{-0.09}^*$ (−1.97)	$\mathbf{-0.13}^*$ (−3.79)	−0.05 (−1.59)	0.028
$dy_{t+1}^{(2\ y)}$	a	0.12 (0.96)							0.000
	b		−0.00 (−0.06)	0.00 (0.66)	0.00 (0.38)				0.000
	c					$\mathbf{-0.09}$ (−1.74)	$\mathbf{-0.13}^*$ (−2.98)	−0.05 (−1.62)	0.020
	d	0.11 (0.94)				$\mathbf{-0.09}$ (−1.71)	$\mathbf{-0.13}^*$ (−2.93)	−0.06 (−1.64)	0.019
	e		−0.00 (−0.56)	0.00 (0.60)	0.01 (0.76)	$\mathbf{-0.09}$ (−1.76)	$\mathbf{-0.13}^*$ (−2.95)	$\mathbf{-0.06}$ (−1.73)	0.018
$dy_{t+1}^{(3\ y)}$	a	0.02 (0.19)							0.000
	b		−0.00 (−0.23)	0.00 (0.52)	0.01 (1.20)				0.000
	c					−0.07 (−1.57)	$\mathbf{-0.12}^*$ (−2.75)	−0.05 (−1.32)	0.014
	d	0.02 (0.25)				−0.07 (−1.31)	$\mathbf{-0.12}^*$ (−2.53)	−0.05 (−1.56)	0.013
	e		−0.00 (−0.70)	0.00 (0.48)	0.01 (1.62)	−0.07 (−1.39)	$\mathbf{-0.12}^*$ (−2.53)	$\mathbf{-0.05}$ (−1.74)	0.014
$dy_{t+1}^{(4\ y)}$	a	−0.01 (−0.11)							0.000
	b		−0.00 (−0.28)	0.00 (0.62)	0.01 (1.61)				0.001
	c					−0.04 (−0.87)	$\mathbf{-0.12}*$ (−2.33)	$\mathbf{-0.05}$ (−1.77)	0.011
	d	−0.00 (−0.02)				−0.04 (−0.87)	$\mathbf{-0.12}*$ (−2.33)	$\mathbf{-0.05}$ (−1.75)	0.011
	e		−0.00 (−0.65)	0.00 (0.61)	$\mathbf{0.02}$ (1.87)	−0.05 (−0.97)	$\mathbf{-0.12}*$ (−2.33)	$\mathbf{-0.06}*$ (−1.98)	0.013
$dy_{t+1}^{(5\ y)}$	a	−0.02 (−0.28)							0.000
	b		−0.00 (−0.23)	0.00 (0.80)	0.01 (1.48)				0.000
	c					−0.02 (−0.46)	$\mathbf{-0.11}*$ (−2.20)	$\mathbf{-0.06}*$ (−2.17)	0.010
	d	−0.01 (−0.18)				−0.02 (−0.46)	$\mathbf{-0.11}*$ (−2.21)	$\mathbf{-0.06}*$ (−2.14)	0.010
	e		−0.00 (−0.57)	0.00 (0.82)	$\mathbf{0.01}$ (1.75)	−0.02 (−0.55)	$\mathbf{-0.11}*$ (−2.20)	$\mathbf{-0.07}*$ (−2.40)	0.012
$dy_{t+1}^{(10\ y)}$	a	−0.07 (−1.00)							0.000
	b		0.00 (0.04)	$\mathbf{0.00}$ (1.68)	$\mathbf{-0.02}$ (1.90)				0.003
	c					0.03 (0.74)	−0.06 (−1.54)	$\mathbf{-0.11}*$ (−4.01)	0.013
	d	−0.19 (−1.21)				0.02 (0.67)	−0.06 (−1.50)	$\mathbf{-0.10}*$ (−4.15)	0.013
	e		−0.00 (−0.25)	$\mathbf{0.00}$ (1.86)	$\mathbf{-0.01}$ (−1.85)	0.03 (0.88)	−0.06 (−1.45)	$\mathbf{-0.11}*$ (−4.12)	0.016

Table 8
In-sample predictions of daily excess returns

The table displays the results of the in-sample predictions of excess returns at a daily horizon, where $exr_{t+1}^{(i\ y)}$ is daily excess returns 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. The forecasts are based on models a), b), c), d) and e) presented in equations (13) - (17). Coefficients are multiplied with 100 and in bold when significant at the 10 percent level or better. * 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	$Adj.R^2$
$exr_{t+1}^{(1\ y)}$	a	0.35 (1.51)							0.003
	b		$\mathbf{-0.00}*$ (−8.33)	$\mathbf{-0.01}*$ (−4.32)	−0.00 (−0.25)				0.053
	c					$\mathbf{0.10}*$ (2.19)	$\mathbf{0.12}*$ (3.45)	$\mathbf{0.07}*$ (2.14)	0.030
	d	$\mathbf{0.40}$ (1.76)				$\mathbf{0.10}*$ (2.27)	$\mathbf{0.12}*$ (3.73)	$\mathbf{0.05}$ (1.68)	0.034
	e		$\mathbf{-0.00}*$ (−7.92)	$\mathbf{-0.01}*$ (−4.52)	−0.00 (−0.64)	$\mathbf{0.07}$ (1.70)	$\mathbf{0.12}*$ (3.56)	$\mathbf{0.06}$ (1.92)	0.078
$exr_{t+1}^{(2\ y)}$	a	$\mathbf{0.53}*$ (2.24)							0.003
	b		$\mathbf{-0.00}*$ (−3.41)	$\mathbf{-0.01}$ (−1.83)	−0.01 (−0.83)				0.007
	c					$\mathbf{0.18}$ (1.80)	$\mathbf{0.24}*$ (2.82)	$\mathbf{0.12}$ (1.92)	0.020
	d	$\mathbf{0.54}*$ (2.38)				$\mathbf{0.18}$ (1.86)	$\mathbf{0.25}*$ (2.95)	0.11 (1.61)	0.023
	e		$\mathbf{-0.00}*$ (−3.13)	$\mathbf{-0.01}$ (−1.87)	−0.02 (−1.19)	0.16 (1.63)	$\mathbf{0.24}*$ (2.84)	$\mathbf{0.12}$ (1.90)	0.026
$exr_{t+1}^{(3\ y)}$	a	$\mathbf{0.56}*$ (2.05)							0.002
	b		$\mathbf{-0.00}*$ (−2.02)	−0.01 (−1.30)	−0.04 (−1.59)				0.004
	c					0.19 (1.35)	$\mathbf{0.35}*$ (2.45)	$\mathbf{0.16}$ (1.79)	0.014
	d	$\mathbf{0.55}*$ (2.13)				0.19 (1.36)	$\mathbf{0.36}*$ (2.52)	0.15 (1.58)	0.016
	e		$\mathbf{-0.00}$ (−1.75)	−0.01 (−1.31)	$\mathbf{-0.05}$ (−1.88)	0.19 (1.29)	$\mathbf{0.35}*$ (2.47)	$\mathbf{0.17}$ (1.86)	0.018
$exr_{t+1}^{(4\ y)}$	a	$\mathbf{0.59}$ (1.84)							0.002
	b		−0.00 (−1.45)	−0.01 (−1.23)	$\mathbf{-0.06}$ (−1.81)				0.003
	c					0.16 (0.89)	$\mathbf{0.43}*$ (2.26)	$\mathbf{0.22}$ (1.95)	0.011
	d	$\mathbf{0.56}$ (1.86)				0.16 (0.88)	$\mathbf{0.44}*$ (2.32)	$\mathbf{0.21}$ (1.79)	0.013
	e		−0.00 (−1.20)	−0.01 (−1.25)	$\mathbf{-0.07}*$ (−2.08)	0.16 (0.88)	$\mathbf{0.43}*$ (2.28)	$\mathbf{0.23}*$ (2.08)	0.015
$exr_{t+1}^{(5\ y)}$	a	$\mathbf{0.63}$ (1.71)							0.001
	b		−0.00 (−1.18)	−0.01 (−1.30)	$\mathbf{-0.07}$ (−1.65)				0.002
	c					0.10 (0.48)	$\mathbf{0.50}*$ (2.14)	$\mathbf{0.31}*$ (2.32)	0.011
	d	$\mathbf{0.59}$ (1.68)				0.10 (0.47)	$\mathbf{0.51}*$ (2.20)	$\mathbf{0.30}*$ (2.18)	0.012
	e		−0.00 (−0.94)	−0.01 (−1.35)	$\mathbf{-0.07}$ (−1.92)	0.10 (−0.63)	$\mathbf{0.50}*$ (2.16)	$\mathbf{0.33}*$ (2.48)	0.013
$exr_{t+1}^{(10\ y)}$	a	$\mathbf{1.17}$ (1.75)							0.002
	b		−0.00 (−0.77)	$\mathbf{-0.03}$ (1.96)	$\mathbf{0.15}$ (1.81)				0.004
	c					−0.24 (−0.71)	0.59 (1.51)	$\mathbf{1.04}*$ (4.07)	0.013
	d	1.01 (1.57)				−0.25 (−0.74)	0.61 (1.55)	$\mathbf{1.00}*$ (3.98)	0.015
	e		−0.003 (−0.53)	$\mathbf{-0.04}*$ (−2.15)	$\mathbf{0.13}$ (1.75)	−0.31 (−0.92)	0.57 (1.44)	$\mathbf{1.03}*$ (4.15)	0.017

Table 9
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), 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**∗							0.090
		(2.57)							
	b		0.00	0.05	**0.16**∗				0.000
			(0.05)	(0.98)	(2.02)				
	c					**−0.30**∗	**−0.22**∗	0.12	0.167
						(−2.61)	(−2.31)	(1.21)	
	d	6.58				**−0.24**∗	**−0.20**	0.07	0.182
		(1.55)				(−2.34)	(−1.86)	(0.64)	
	e		−0.01	0.01	**0.24**∗	**−0.33**∗	**−0.22**∗	0.11	0.184
			(−0.59)	(0.34)	(2.15)	(−3.01)	(−2.08)	(1.03)	
$dy_{t+1}^{(2\ years)}$	a	2.44							0.000
		(0.82)							
	b		−0.00	0.02	**0.25**∗				0.001
			(−0.34)	(0.43)	(2.29)				
	c					**−0.23**∗	**−0.28**∗	0.07	0.113
						(−2.12)	(−2.12)	(0.70)	
	d	0.71				**−0.23**∗	**−0.27**∗	0.01	0.101
		(0.26)				(−2.07)	(−2.04)	(0.59)	
	e		−0.01	−0.01	**0.33**∗	**−0.29**∗	**−0.28**∗	0.06	0.154
			(−0.99)	(−0.23)	(2.34)	(−2.45)	(−1.99)	(0.56)	
$dy_{t+1}^{(3\ years)}$	a	0.57							0.000
		(0.24)							
	b		−0.01	0.02	**0.28**∗				0.012
			(−0.43)	(0.42)	(2.42)				
	c					**−0.18**	**−0.28**	0.04	0.085
						(−1.75)	(−1.95)	(0.41)	
	d	0.01				**−0.18**	**−0.28**	0.04	0.072
		(0.00)				(−1.74)	(−1.95)	(0.39)	
	e		−0.01	−0.01	**0.35**∗	**−0.24**∗	**−0.28**	0.02	0.137
			(−1.02)	(−0.14)	(2.47)	(−2.07)	(−1.88)	(0.16)	
$dy_{t+1}^{(4\ years)}$	a	−0.04							0.000
		(−0.02)							
	b		−0.01	0.03	**0.27**∗				0.016
			(−0.42)	(0.55)	(2.53)				
	c					−0.15	**−0.27**	0.02	0.073
						(−1.48)	(−1.90)	(0.22)	
	d	−0.26				−0.14	**−0.27**	0.02	0.060
		(−0.14)				(−1.49)	(−1.94)	(0.24)	
	e		−0.01	0.00	**0.34**∗	**−0.20**	**−0.27**	−0.00	0.125
			(−0.92)	(0.07)	(2.61)	(−1.81)	(−1.84)	(−0.05)	
$dy_{t+1}^{(5\ years)}$	a	−0.35							0.000
		(−0.19)							
	b		−0.00	0.03	**0.25**∗				0.014
			(−0.37)	(0.71)	(2.56)				
	c					−0.12	**−0.26**	0.01	0.069
						(−1.29)	(−1.90)	(0.08)	
	d	−0.44				−0.12	**−0.27**∗	0.01	0.057
		(−0.26)				(−1.29)	(−1.97)	(0.12)	
	e		−0.01	0.01	**0.31**∗	−0.17	**−0.26**	−0.02	0.115
			(−0.84)	(0.31)	(2.74)	(−1.60)	(−1.85)	(−0.12)	
$dy_{t+1}^{(10\ years)}$	a	−1.09							0.000
		(−0.69)							
	b		−0.00	0.06	0.07				0.000
			(−0.26)	(1.60)	(0.90)				
	c					−0.07	**−0.25**	−0.02	0.060
						(−0.72)	(−1.85)	(−0.29)	
	d	−1.09				−0.06	**−0.26**∗	−0.01	0.055
		(−0.71)				(−0.67)	(−2.00)	(−0.14)	
	e		−0.01	0.05	**0.11**	−0.09	**−0.23**	−0.06	0.054
			(−0.62)	(1.61)	(1.76)	(−0.86)	(−1.69)	(−0.61)	

Table 10

In-sample predictions of monthly excess returns. Non-overlapping data

The table displays the results of the in-sample predictions of excess returns at the monthly horizon, where $exr_{t+1}^{(i\ y)}$ is monthly excess returns 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. The forecasts are based on models a), b), c), d) and e) presented in equations (13) - (17). Coefficients are multiplied with 100 and in bold when significant at the 10 percent level or better. * indicates that the coefficients are significant at the 5 percent level or better.

	model	FS_t	$F1_t$	$F2_t$	$F3_t$	OF_t^S	OF_t^M	OF_t^L	$Adj.R^2$
$exr_{t+1}^{(1\ year)}$	*a*	6.60 (1.03)							0.011
	b		**−0.07**∗ (−6.12)	**−0.15**∗ (−3.39)	**−0.29**∗ (−3.17)				0.411
	c					**0.39**∗ (2.62)	0.10 (0.55)	0.02 (0.12)	0.124
	d	**14.83**∗ (2.85)				**0.51**∗ (4.05)	0.15 (1.08)	−0.12 (−0.91)	0.214
	e		**−0.07**∗ (−6.54)	**−0.12**∗ (−3.35)	**−0.35**∗ (−2.93)	**0.22** (1.93)	**0.21** (1.92)	−0.03 (−0.30)	0.478
$exr_{t+1}^{(2\ years)}$	*a*	**10.29** (1.69)							0.029
	b		**−0.06**∗ (−2.34)	−0.14 (−1.41)	**−0.63**∗ (−2.70)				0.109
	c					**0.55**∗ (2.32)	0.43 (1.42)	0.00 (0.00)	0.110
	d	**14.25**∗ (2.72)				**0.61**∗ (2.92)	**0.52**∗ (1.98)	−0.14 (−0.67)	0.175
	e		**−0.05** (−1.95)	−0.09 (−1.08)	**−0.77**∗ (−2.61)	**0.47** (1.95)	**0.55** (1.91)	−0.02 (−0.11)	0.218
$exr_{t+1}^{(3\ years)}$	*a*	10.87 (1.56)							0.023
	b		−0.05 (−1.37)	−0.16 (−1.10)	**−0.96**∗ (−2.66)				0.061
	c					**0.63** (1.94)	0.70 (1.54)	0.02 (0.07)	0.085
	d	**12.57**∗ (2.02)				**0.64**∗ (2.15)	**0.79** (1.91)	−0.11 (−0.35)	0.121
	e		−0.03 (−0.84)	−0.09 (−0.73)	**−1.16**∗ (−2.67)	**0.62** (1.74)	**0.82** (1.82)	−0.02 (−0.06)	0.162
$exr_{t+1}^{(4\ years)}$	*a*	11.53 (1.44)							0.018
	b		−0.05 (−0.97)	−0.20 (−1.09)	**−1.21**∗ (−2.72)				0.049
	c					**0.67** (1.66)	0.95 (1.59)	0.06 (0.15)	0.074
	d	**12.29** (1.67)				**0.65** (1.72)	**1.04** (1.89)	−0.07 (−0.17)	0.097
	e		−0.02 (−0.45)	−0.12 (−0.77)	**−1.45**∗ (−2.76)	0.70 (1.55)	**1.07** (1.80)	0.08 (0.22)	0.141
$exr_{t+1}^{(5\ years)}$	*a*	12.58 (1.36)							0.017
	b		−0.05 (−0.78)	−0.25 (−1.18)	**−1.36**∗ (−2.74)				0.041
	c					0.69 (1.45)	**1.20** (1.65)	0.10 (0.22)	0.070
	d	12.89 (1.50)				0.65 (1.44)	**1.30** (1.92)	−0.03 (−0.06)	0.089
	e		−0.02 (−0.24)	−0.17 (−0.94)	**−1.64**∗ (−2.90)	0.74 (1.39)	**1.30** (1.80)	0.16 (0.35)	0.128
$exr_{t+1}^{(10\ years)}$	*a*	21.29 (1.35)							0.018
	b		−0.04 (−0.40)	**−0.66** (−1.88)	−0.82 (−1.06)				0.005
	c					0.75 (0.82)	**2.39** (1.72)	0.39 (0.44)	0.060
	d	21.14 (1.37)				0.66 (0.72)	**2.55**∗ (1.98)	0.17 (0.18)	0.078
	e		0.01 (0.10)	**−0.58**∗ (−2.06)	**−1.23** (−2.00)	0.83 (0.82)	2.22 (1.64)	0.63 (0.84)	0.073

Table 11
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). 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 12
Out-of-Sample predictions of daily bond excess returns

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). 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
$exr^{(1Y)}_{t+1}$	OF^S, OF^M, OF^L	0.970	**36.57***
	$F1, F2$	0.950	**68.14***
$exr^{(2Y)}_{t+1}$	OF^S, OF^M, OF^L	0.982	**23.36***
	$F1, F2$	0.998	**1.92***
$exr^{(3Y)}_{t+1}$	OF^M, OF^L	0.989	**13.90***
	$F1$	1.005	-5.57
$exr^{(4Y)}_{t+1}$	OF^M, OF^L	0.991	**11.75***
	$F3$	0.998	**2.18***
$exr^{(5Y)}_{t+1}$	OF^M, OF^L	0.991	**11.57***
	$F3$	0.999	**1.63***
$exr^{(10Y)}_{t+1}$	OF^L	0.987	**17.06***
	$F2$, $F3$	0.998	**2.99***

Table 13
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). 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 14
Out-of-Sample predictions of monthly bond excess returns

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). 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
$exr_{t+1}^{(1Y)}$	OF^S	0.855	**8.98***
	$F1, F2, F3$	0.637	**30.30***
$exr_{t+1}^{(2Y)}$	OF^S, OF^M	0.896	**6.15***
	$F1, F3$	0.976	**1.28**
$exr_{t+1}^{(3Y)}$	OF^S, OF^M	0.922	**4.49***
	$F3$	0.938	**3.50***
$exr_{t+1}^{(4Y)}$	OF^S, OF^M	0.936	**3.63***
	$F3$	0.939	**3.42***
$exr_{t+1}^{(5Y)}$	OF^M	0.931	**3.91***
	$F3$	0.946	**3.05***
$exr_{t+1}^{(10Y)}$	OF^M	0.937	**3.59***
	$F2$	0.971	**1.60***

Table 15
In-sample predictions of daily yield changes based on informed customer order flow and orthogonal interdealer order flow

The table presents the results of regressing yield changes on day t+1 on the proxy for informed customer order flow, $HCOF_t^S$, $HCOF_t^M$ and $HCOF_t^L$,and orthogonal interdealer order flow, $resOF_t^S$,$resOF_t^M$ and $resOF_t^L$, at time t. The regressions also include a constant and the three first forward rate factors at time t, but the coefficients are dropped from the table. Coefficients are multiplied with 100 and in bold when significant at the 10 percent level. * indicates significance at the 5 percent level or better.

	model	$HCOF_t^S$	$resOF_t^S$	$HCOF_t^M$	$resOF_t^M$	$HCOF_t^L$	$resOF_t^L$	$Adj.R^2$
dy_{t+1}^{1y}	k	−0.06 (−1.31)		−0.07 (−1.38)		−0.03 (−0.57)		0.003
	l		**−0.08** (−1.96)		**−0.12**∗ (−3.47)		−0.05 (−1.49)	0.026
	m	−0.06 (−1.38)	**−0.08** (−1.95)	−0.07 (−1.40)	**−0.12**∗ (−3.46)	−0.03 (−0.61)	−0.05 (−1.55)	0.029
dy_{t+1}^{2y}	k	−0.06 (−1.24)		**−0.10** (−1.89)		−0.07 (−1.22)		0.003
	l		**−0.08** (−1.72)		**−0.12**∗ (−2.69)		−0.05 (−1.64)	0.016
	m	−0.06 (−1.29)	**−0.08** (−1.73)	**−0.10** (−1.93)	**−0.12**∗ (−2.69)	−0.07 (−1.29)	**−0.06** (−1.75)	0.021
dy_{t+1}^{3y}	k	−0.04 (−0.80)		**−0.12**∗ (−2.13)		−0.08 (−1.25)		0.004
	l		−0.07 (−1.36)		**−0.11**∗ (−2.32)		**−0.05** (−1.77)	0.013
	m	−0.04 (−0.84)	−0.06 (−1.35)	**−0.12**∗ (−2.16)	**−0.11**∗ (−2.33)	−0.08 (−1.32)	**−0.05** (−1.92)	0.017
dy_{t+1}^{4y}	k	−0.02 (−0.44)		**−0.12**∗ (−2.19)		−0.08 (−1.32)		0.004
	l		−0.04 (−0.95)		**−0.10**∗ (−2.14)		**−0.05**∗ (−2.11)	0.011
	m	−0.03 (−0.48)	−0.04 (−0.94)	**−0.12**∗ (−2.23)	**−0.10**∗ (−2.15)	−0.08 (−1.37)	**−0.06**∗ (−2.29)	0.015
dy_{t+1}^{5y}	k	−0.01 (−0.17)		**−0.12**∗ (−2.16)		−0.09 (−1.48)		0.004
	l		−0.02 (−0.57)		**−0.09**∗ (−2.02)		**−0.06**∗ (−2.58)	0.010
	m	−0.01 (−0.20)	−0.02 (−0.55)	**−0.12**∗ (−2.21)	**−0.09**∗ (−2.04)	−0.09 (−1.54)	**−0.06**∗ (−2.77)	0.014
dy_{t+1}^{10y}	k	0.03 (0.70)		−0.08 (−1.57)		**−0.12**∗ (−2.47)		0.009
	l		0.03 (0.79)		−0.05 (−1.31)		**−0.09**∗ (−4.10)	0.014
	m	0.03 (0.64)	0.03 (0.84)	**−0.09** (−1.73)	−0.05 (−1.32)	**−0.12**∗ (−2.54)	**−0.10**∗ (−4.16)	0.020

Table 16
In-sample predictions of daily excess returns based on informed customer order flow and orthogonal interdealer order flow

The table presents the results of regressing excess returns on day t+1 on the proxy for informed customer order flow, $HCOF_t^S$, $HCOF_t^M$ and $HCOF_t^L$,and orthogonal interdealer order flow, $resOF_t^S$,$resOF_t^M$ and $resOF_t^L$, at time t. The regressions also include a constant and the three first forward rate factors at time t, but the coefficients are dropped from the table. Coefficients are multiplied with 100 and in bold when significant at the 10 percent level. * indicates significance at the 5 percent level or better.

	model	$HCOF_t^S$	$resOF_t^S$	$HCOF_t^M$	$resOF_t^M$	$HCOF_t^L$	$resOF_t^L$	$Adj.R^2$
exr_{t+1}^{1y}	k	0.05		0.06		0.03		0.030
		(1.24)		(1.25)		(0.71)		
	l		**0.07**		**0.12**$*$		**0.05**	0.053
			(1.78)		(3.38)		(1.69)	
	m	0.05	**0.07**	0.06	**0.12**$*$	0.03	**0.06**	0.055
		(1.32)	(1.78)	(1.29)	(3.37)	(0.76)	(1.74)	
exr_{t+1}^{2y}	k	0.12		**0.20**		0.15		0.007
		(1.20)		(1.82)		(1.27)		
	l		**0.16**		**0.23**$*$		**0.11**	0.020
			(1.65)		(2.65)		(1.74)	
	m	0.12	**0.16**	**0.20**	**0.23**$*$	0.15	**0.12**	0.025
		(1.26)	(1.66)	(1.87)	(2.65)	(1.35)	(1.85)	
exr_{t+1}^{3y}	k	0.13		**0.35**$*$		0.24		0.006
		(0.77)		(2.08)		(1.27)		
	l		0.19		**0.33**$*$		**0.15**	0.014
			(1.30)		(2.30)		(1.85)	
	m	0.13	0.18	**0.35**$*$	**0.33**$*$	0.24	**0.16**$*$	0.018
		(0.81)	(1.30)	(2.12)	(2.30)	(1.35)	(2.00)	
exr_{t+1}^{4y}	k	0.09		**0.47**$*$		0.33		0.006
		(0.42)		(2.16)		(1.34)		
	l		0.16		**0.41**$*$		**0.21**$*$	0.012
			(0.91)		(2.12)		(2.17)	
	m	0.10	0.16	**0.48**$*$	**0.40**$*$	0.33	**0.23**$*$	0.016
		(0.45)	(0.90)	(2.19)	(2.13)	(1.40)	(2.35)	
exr_{t+1}^{5y}	k	0.04		**0.57**$*$		0.43		0.005
		(0.15)		(2.13)		(1.51)		
	l		0.11		**0.47**$*$		**0.30**$*$	0.011
			(0.53)		(2.00)		(2.64)	
	m	0.05	0.10	**0.59**$*$	**0.46**$*$	0.43	**0.32**$*$	0.015
		(0.18)	(0.51)	(2.18)	(2.02)	(1.57)	(2.82)	
exr_{t+1}^{10y}	k	−0.29		0.84		**1.19**$*$		0.010
		(−0.72)		(1.56)		(2.49)		
	l		−0.27		0.53		**0.95**$*$	0.015
			(−0.82)		(1.31)		(4.13)	
	m	−0.27	−0.27	**0.92**	0.51	**1.19**$*$	**0.98**$*$	0.021
		(−0.65)	(−0.86)	(1.71)	(1.31)	(2.55)	(4.18)	

Table 17
In-sample predictions of monthly yield changes based on delayed publication customer order flow and orthogonal interdealer order flow

The table presents the results of regressing yield changes on month t+1 on the proxy for informed customer order flow, $HCOF_t^S$, $HCOF_t^M$ and $HCOF_t^L$,and orthogonal interdealer order flow, $resOF_t^S$, $resOF_t^M$ and $resOF_t^L$, the previous month. The regressions also include a constant and the three first forward rate factors at time t, but the coefficients are dropped from the table. Coefficients are multiplied with 100 and in bold when significant at the 10 percent level. * indicates significance at the 5 percent level or better.

	model	$HCOF_t^S$	$resOF_t^S$	$HCOF_t^M$	$resOF_t^M$	$HCOF_t^L$	$resOF_t^L$	$Adj.R^2$
dy_{t+1}^{1y}	k	−0.08 (−0.53)		**−0.41**∗ (−2.15)		0.16 (1.02)		0.029
	l		**−0.38**∗ (−3.30)		−0.14 (−1.24)		0.12 (1.00)	0.146
	m	−0.03 (−0.22)	**−0.33**∗ (−2.73)	**−0.38**∗ (−2.16)	−0.17 (−1.40)	0.08 (0.57)	0.10 (0.77)	0.163
dy_{t+1}^{2y}	k	−0.08 (−0.67)		**−0.39** (1.90)		0.00 (0.02)		0.021
	l		**−0.34**∗ (−2.93)		−0.21 (−1.42)		0.11 (0.90)	0.128
	m	−0.03 (−0.25)	**−0.31**∗ (−2.54)	**−0.37** (−1.88)	−0.23 (−1.42)	−0.07 (−0.40)	0.09 (0.67)	0.140
dy_{t+1}^{3y}	k	−0.08 (−0.78)		**−0.37** (−1.94)		−0.09 (−0.49)		0.038
	l		**−0.30**∗ (−2.62)		−0.20 (−1.35)		0.10 (0.83)	0.111
	m	−0.03 (−0.33)	**−0.28**∗ (−2.33)	**−0.36** (−1.86)	−0.22 (−1.31)	−0.16 (−0.89)	0.08 (0.60)	0.133
dy_{t+1}^{4y}	k	−0.08 (−0.82)		**−0.35**∗ (−1.99)		−0.15 (−0.89)		0.053
	l		**−0.25**∗ (−2.39)		−0.19 (−1.34)		0.09 (0.79)	0.097
	m	−0.04 (−0.39)	**−0.24**∗ (−2.16)	**−0.34** (−1.85)	−0.20 (−1.27)	−0.21 (−1.26)	0.07 (0.55)	0.133
dy_{t+1}^{5y}	k	−0.09 (−0.82)		**−0.33**∗ (−2.01)		−0.19 (−1.22)		0.063
	l		**−0.22**∗ (−2.18)		−0.19 (−1.35)		0.09 (0.74)	0.084
	m	−0.05 (−0.42)	**−0.21**∗ (−2.00)	**−0.33** (−1.83)	−0.19 (−1.26)	−0.24 (−1.58)	0.06 (0.50)	0.134
dy_{t+1}^{10y}	k	−0.11 (−0.85)		**−0.24** (−1.65)		**−0.28**∗ (−2.32)		0.069
	l		−0.12 (−1.23)		−0.17 (−1.33)		0.05 (0.50)	0.016
	m	−0.07 (−0.57)	−0.13 (−1.25)	−0.24 (−1.44)	−0.16 (−1.16)	**−0.32**∗ (−2.59)	0.03 (0.30)	0.100

Table 18
In-sample predictions of monthly excess returns based on delayed publication customer order flow and orthogonal interdealer order flow

The table presents the results of regressing excess returns on month t+1 on the proxy for informed customer order flow, $HCOF_t^S$, $HCOF_t^M$ and $HCOF_t^L$,and orthogonal interdealer order flow, $resOF_t^S$, $resOF_t^M$ and $resOF_t^L$, the previous month. The regressions also include a constant and the three first forward rate factors at time t, but the coefficients are dropped from the table. Coefficients are multiplied with 100 and in bold when significant at the 10 percent level. * indicates significance at the 5 percent level or better.

	model	$HCOF_t^S$	$resOF_t^S$	$HCOF_t^M$	$resOF_t^M$	$HCOF_t^L$	$resOF_t^L$	$Adj.R^2$
exr_{t+1}^{1y}	k	−0.00		**0.32**		−0.07		0.401
		(−0.03)		(1.90)		(−0.45)		
	l		**0.26**$\ast$		0.16		−0.07	0.457
			(2.15)		(1.40)		(−0.58)	
	m	−0.05	**0.23**	**0.31**$\ast$	0.19	−0.01	−0.05	0.451
		(−0.39)	(1.89)	(2.03)	(1.50)	(−0.06)	(−0.38)	
exr_{t+1}^{2y}	k	0.08		**0.69**		0.09		0.110
		(0.35)		(1.77)		(0.24)		
	l		**0.56**$\ast$		0.43		−0.18	0.193
			(2.33)		(1.48)		(−0.69)	
	m	−0.02	**0.52**$\ast$	0.68	0.46	0.22	−0.13	0.193
		(−0.10)	(2.11)	(1.80)	(1.46)	(0.62)	(−0.47)	
exr_{t+1}^{3y}	k	0.16		**1.02**		0.37		0.076
		(0.52)		(1.85)		(0.68)		
	l		**0.76**$\ast$		0.62		−0.26	0.136
			(2.20)		(1.39)		(−0.69)	
	m	0.02	**0.73**$\ast$	**1.00**	0.66	0.55	−0.18	0.150
		(0.07)	(2.03)	(1.79)	(1.33)	(1.05)	(−0.46)	
exr_{t+1}^{4y}	k	0.25		**1.32**		0.70		0.077
		(0.61)		(1.92)		(1.04)		
	l		**0.89**$\ast$		0.79		−0.32	0.112
			(2.05)		(1.37)		(−0.67)	
	m	0.08	**0.86**	**1.30**	0.82	0.91	−0.22	0.141
		(0.20)	(1.92)	(1.80)	(1.28)	(1.39)	(−0.44)	
exr_{t+1}^{5y}	k	0.35		**1.58**		1.03		0.082
		(0.65)		(1.95)		(1.36)		
	l		**0.97**		0.96		−0.37	0.096
			(1.90)		(1.38)		(−0.64)	
	m	0.15	**0.95**	**1.56**	0.98	**1.27**	−0.25	0.140
		(0.27)	(1.79)	(1.78)	(1.28)	(1.68)	(−0.41)	
exr_{t+1}^{10y}	k	0.97		2.26		**2.94**$\ast$		0.079
		(0.77)		(1.60)		(2.41)		
	l		1.08		1.71		−0.47	0.024
			(1.09)		(1.34)		(−0.44)	
	m	0.67	1.17	2.30	1.63	**3.24**$\ast$	−0.29	0.103
		(0.50)	(1.15)	(1.40)	(1.17)	(2.66)	(−0.26)	

Table 19
Out-of-Sample predictions of daily yield changes based on delayed publication customer order flow and orthogonal interdealer order flow

The table compares the out-of-sample predictive power of models based on informed customer order flow and models based on orthogonal interdealer order flow to the random walk (RW). 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
$dy_{t+1}^{(1Y)}$	$resOF^S, resOF^M$	0.976	**30.74***
$dy_{t+1}^{(2Y)}$	$resOF^S, resOF^M$	0.985	**19.01***
	$HCOF^M$	1.00	**0.73**
$dy_{t+1}^{(3Y)}$	$resOF^M, resOF^L$	0.992	**10.85***
	$HCOF^M$	0.999	**1.20**
$dy_{t+1}^{(4Y)}$	$resOF^M, resOF^L$	0.993	**8.90***
	$HCOF^M$	0.999	**1.20**
$dy_{t+1}^{(5Y)}$	$resOF^M, resOF^L$	0.993	**8.63***
	$HCOF^M$	0.999	**0.85**
$dy_{t+1}^{(10Y)}$	$resOF^L$	0.989	**13.57***
	$HCOF^L$	0.998	**1.98***

Table 20
Out-of-Sample predictions of daily excess returns based on delayed publication customer order flow and orthogonal interdealer order flow

The table compares the out-of-sample predictive power of models based on informed customer order flow and models based on orthogonal interdealer order flow to the random walk (RW). 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
$exr_{t+1}^{(1Y)}$	$resOF^S, resOF^M, resOF^L$	0.975	**32.88***
$exr_{t+1}^{(2Y)}$	$resOF^S, resOF^M, resOF^L$	0.985	**19.72***
	$HCOF^M$	0.999	**0.87**
$exr_{t+1}^{(3Y)}$	$resOF^M, resOF^L$	0.991	**11.07***
	$HCOF^M$	0.999	**1.31**
$exr_{t+1}^{(4Y)}$	$resOF^M, resOF^L$	0.993	**9.09***
	$HCOF^M$	0.999	**1.20**
$exr_{t+1}^{(5Y)}$	$resOF^M, resOF^L$	0.993	**8.84***
	$HCOF^M$	0.999	**0.92**
$exr_{t+1}^{(10Y)}$	$resOF^L$	0.989	**13.89***
	$HCOF^L$	0.998	**2.43***

Table 21
Out-of-Sample predictions of monthly yield changes based on delayed publication customer order flow and orthogonal interdealer order flow

The table compares the out-of-sample predictive power of models based on informed customer order flow and models based on orthogonal interdealer order flow to the random walk (RW). 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
$dy_{t+1}^{(1Y)}$	$resOF^S$	0.892	**6.44***
	$HCOF^M$	1.006	-0.28
$dy_{t+1}^{(2Y)}$	$resOF^S$	0.921	**4.60***
	$HCOF^M$	1.044	-2.18
$dy_{t+1}^{(3Y)}$	$resOF^S$	0.942	**3.32***
	$HCOF^M$	1.047	-2.34
$dy_{t+1}^{(4Y)}$	$resOF^S$	0.952	**2.67***
	$HCOF^M$	1.041	-2.09
$dy_{t+1}^{(5Y)}$	$resOF^S$	0.959	**2.32***
	$HCOF^M$	1.033	-1.75
$dy_{t+1}^{(10Y)}$	$resOF^S$	0.986	0.77
	$HCOF^M$,$HCOF^L$	1.043	-2.18

Table 22
Out-of-Sample predictions of monthly excess returns based on delayed publication customer order flow and orthogonal interdealer order flow

The table compares the out-of-sample predictive power of models based on informed customer order flow and models based on orthogonal interdealer order flow to the random walk (RW). 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
$exr_{t+1}^{(1Y)}$	$resOF^S$	0.821	**11.57***
	$HCOF^M$	0.990	0.55
$exr_{t+1}^{(2Y)}$	$resOF^S$	0.870	**7.94***
	$HCOF^M$	1.029	-1.47
$exr_{t+1}^{(3Y)}$	$resOF^S$	0.909	**5.29***
	$HCOF^M$	1.037	-1.89
$exr_{t+1}^{(4Y)}$	$resOF^S$	0.930	**4.02***
	$HCOF^M$	1.034	-1.76
$exr_{t+1}^{(5Y)}$	$resOF^S$	0.941	**3.35***
	$HCOF^M$	1.073	-3.60
$exr_{t+1}^{(10Y)}$	$resOF^S$	0.979	1.16
	$HCOF^L$	0.998	0.09

Table 23
Dealer characteristics

The table describes the seven dealers who were active in the government bond market during the period 1999 - 2005. They are characterized by size, customer base, interdealer 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. Interdealer 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	Interdealer 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

Table 24
Composition of dealer trades

The table shows the composition of trades for each of the seven dealers during the period 1999 - 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 25
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. 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	$OF^S_{i,t}$	$OF^M_{i,t}$	$OF^L_{i,t}$	$Adj.R^2$
dy^{1y}_{t+1}	1	**−0.24**∗	**−0.50**∗	−0.07	0.023
		(−2.46)	(−3.05)	(−0.99)	
	2	−0.09	−0.10	−0.10	0.001
		(−0.65)	(−1.23)	(−1.10)	
	3	−0.12	−0.14	−0.05	0.003
		(−0.84)	(−1.60)	(−0.73)	
	4	−0.06	**−0.17**	**−0.20**∗	0.006
		(−0.50)	(−1.73)	(−2.24)	
	5	−0.13	**−0.17**∗	−0.10	0.005
		(−1.20)	(−2.04)	(−0.72)	
	6	−0.24	−0.10	−0.18	0.002
		(−1.22)	(−0.52)	(−0.85)	
	7	−0.05	−0.06	−0.08	0.002
		(−0.78)	(−0.93)	(−1.34)	
dy^{2y}_{t+1}	1	**−0.27**∗	**−0.56**∗	−0.07	0.018
		(−2.61)	(−3.57)	(−0.70)	
	2	−0.17	−0.06	−0.11	0.000
		(−1.02)	(−0.48)	(−1.04)	
	3	−0.07	−0.16	−0.01	0.000
		(−0.41)	(−1.45)	(−0.15)	
	4	−0.10	−0.17	**−0.28**∗	0.006
		(−0.75)	(−1.52)	(−2.89)	
	5	**−0.21**	**−0.19**	−0.11	0.004
		(−1.70)	(−1.92)	(−0.60)	
	6	−0.08	−0.09	−0.07	0.000
		(−0.33)	(−0.46)	(−0.31)	
	7	0.01	0.03	−0.12	0.000
		(0.09)	(0.41)	(−1.51)	
dy^{3y}_{t+1}	1	**−0.23**∗	**−0.53**∗	−0.07	0.015
		(−2.25)	(−4.01)	(−0.74)	
	2	−0.17	−0.05	−0.08	0.000
		(−1.07)	(−0.37)	(−0.72)	
	3	−0.02	−0.16	0.01	0.000
		(−0.14)	(−1.50)	(0.10)	
	4	−0.10	−0.18	**−0.29**∗	0.007
		(−0.70)	(−1.52)	(−3.12)	
	5	**−0.20**	**−0.21**∗	−0.11	0.005
		(−1.67)	(−2.04)	(−0.55)	
	6	−0.00	−0.09	0.02	0.000
		(−0.02)	(−0.54)	(0.09)	
	7	0.02	0.08	−0.11	0.000
		(0.24)	(0.96)	(−1.31)	

Table 26
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. 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	$OF^S_{i,t}$	$OF^M_{i,t}$	$OF^L_{i,t}$	$Adj.R^2$
dy^{4y}_{t+1}	1	**−0.19** (−1.86)	**−0.47**∗ (−3.91)	−0.09 (−0.89)	0.013
	2	−0.16 (−1.12)	−0.06 (−0.42)	−0.07 (−0.60)	0.001
	3	0.02 (0.13)	−0.16 (−1.57)	0.01 (0.08)	0.000
	4	−0.07 (−0.50)	−0.17 (−1.54)	**−0.28**∗ (−3.14)	0.007
	5	−0.17 (−1.52)	**−0.20**∗ (−1.98)	−0.09 (−0.52)	0.005
	6	0.04 (0.18)	−0.09 (−0.66)	0.09 (0.47)	0.000
	7	0.02 (0.25)	0.10 (1.28)	−0.11 (−1.28)	0.001
dy^{5y}_{t+1}	1	−0.16 (−1.58)	**−0.41**∗ (−3.59)	−0.10 (−1.08)	0.011
	2	−0.16 (−1.20)	−0.07 (−0.49)	−0.07 (−0.63)	0.001
	3	0.05 (0.42)	**−0.16** (−1.65)	−0.01 (−0.08)	0.000
	4	−0.04 (−0.25)	−0.16 (−1.54)	**−0.28**∗ (−3.21)	0.007
	5	−0.14 (−1.38)	−0.19 (−1.79)	−0.08 (−0.50)	0.004
	6	0.08 (0.37)	−0.10 (−0.76)	0.15 (0.85)	0.000
	7	0.02 (0.24)	0.12 (1.57)	−0.12 (−1.39)	0.002
dy^{10y}_{t+1}	1	−0.09 (−0.87)	**−0.20** (−1.75)	**−0.17** (−1.69)	0.010
	2	−0.21 (−1.49)	−0.05 (−0.40)	−0.12 (−1.15)	0.008
	3	0.15 (1.54)	**−0.15** (−1.82)	−0.04 (−0.64)	0.006
	4	0.10 (0.70)	−0.11 (−1.11)	**−0.32**∗ (−4.00)	0.014
	5	−0.11 (−1.08)	−0.10 (−0.80)	−0.03 (−0.28)	0.005
	6	0.22 (1.07)	−0.08 (−0.60)	**0.27** (1.83)	0.005
	7	0.02 (0.28)	**0.12**∗ (2.01)	**−0.16** (−1.80)	0.009

Table 27
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. 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	$OF^S_{i,t}$	$OF^M_{i,t}$	$OF^L_{i,t}$	$Adj.R^2$
dy^{1y}_{t+1}	1	**−0.56**∗	**−1.60**∗	−0.26	0.119
		(−2.03)	(−3.18)	(−0.55)	
	2	−0.44	0.54	0.49	0.000
		(−1.13)	(0.76)	(0.98)	
	3	**−0.40**	**−1.24**∗	−0.18	0.086
		(−1.76)	(−3.15)	(−0.53)	
	4	**−1.13**∗	−0.05	−0.26	0.023
		(−2.50)	(−0.09)	(0.56)	
	5	−0.29	**−0.64**	−0.31	0.029
		(−1.49)	(−1.80)	(−0.47)	
	6	−0.37	**−1.28**	0.24	0.000
		(−0.45)	(−1.85)	(0.26)	
	7	−0.11	−0.03	0.09	0.000
		(−0.55)	(−0.08)	(0.49)	
dy^{2y}_{t+1}	1	**−0.56**	**−1.69**∗	−0.08	0.113
		(−1.65)	(−2.83)	(−0.20)	
	2	−0.65	0.06	0.69	0.009
		(−1.58)	(0.08)	(1.24)	
	3	**−0.65**∗	**−1.13**∗	−0.11	0.092
		(−2.12)	(−2.68)	(−0.37)	
	4	**−1.25**∗	−0.09	−0.04	0.032
		(−2.52)	(−0.17)	(−0.09)	
	5	**−0.56**∗	−0.26	−0.56	0.043
		(−2.06)	(−0.65)	(−0.86)	
	6	−0.40	**−1.28**∗	0.50	0.000
		(−0.44)	(−1.99)	(0.47)	
	7	0.10	−0.03	−0.01	0.000
		(0.44)	(−0.09)	(−0.02)	
dy^{3y}_{t+1}	1	−0.50	**−1.61**∗	0.03	0.111
		(−1.49)	(−2.72)	(0.10)	
	2	**−0.76**	−0.29	0.77	0.041
		(−1.78)	(−0.35)	(1.47)	
	3	**−0.72**	**−0.92**∗	−0.06	0.089
		(−1.94)	(−2.16)	(−0.24)	
	4	**−1.28**∗	−0.03	−0.15	0.048
		(−2.70)	(−0.07)	(−0.35)	
	5	**−0.64**	−0.07	−0.62	0.056
		(−1.79)	(−0.17)	(−1.07)	
	6	−0.19	**−1.35**∗	0.82	0.007
		(−0.21)	(−2.20)	(0.75)	
	7	0.20	0.08	−0.08	0.000
		(0.82)	(0.23)	(−0.29)	

Table 28
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. 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	$OF^S_{i,t}$	$OF^M_{i,t}$	$OF^L_{i,t}$	$Adj.R^2$
dy^{4y}_{t+1}	1	−0.46 (−1.43)	**−1.49**∗ (−2.66)	0.08 (0.31)	0.108
	2	**−0.79** (−1.85)	−0.50 (−0.66)	0.76 (1.62)	0.061
	3	**−0.70** (−1.74)	**−0.73** (−1.74)	−0.03 (−0.13)	0.079
	4	**−1.27**∗ (−2.86)	0.05 (0.09)	−0.20 (−0.54)	0.058
	5	−0.63 (−1.54)	−0.00 (−0.01)	−0.60 (−1.21)	0.058
	6	0.00 (0.01)	**−1.42**∗ (−2.40)	1.06 (0.95)	0.017
	7	0.23 (0.88)	0.16 (0.48)	−0.13 (−0.45)	0.006
dy^{5y}_{t+1}	1	−0.44 (−1.41)	**−1.37**∗ (−2.61)	0.11 (0.47)	0.102
	2	**−0.79** (−1.86)	−0.61 (−0.88)	**0.70** (1.65)	0.069
	3	−0.67 (−1.60)	−0.59 (−1.41)	−0.01 (−0.06)	0.067
	4	**−1.24**∗ (−2.95)	0.12 (0.25)	−0.25 (−0.70)	0.061
	5	−0.58 (−1.34)	0.01 (0.02)	−0.56 (−1.30)	0.052
	6	0.17 (0.21)	**−1.49**∗ (−2.60)	1.20 (1.08)	0.023
	7	0.23 (0.84)	0.20 (0.62)	−0.17 (−0.57)	0.017
dy^{10y}_{t+1}	1	−0.41 (−1.30)	**−0.94**∗ (−2.12)	0.13 (0.63)	0.047
	2	**−0.69** (−1.65)	−0.76 (−1.45)	0.38 (1.10)	0.043
	3	−0.52 (−1.21)	−0.21 (−0.47)	−0.01 (−0.02)	0.000
	4	**−1.16**∗ (−3.06)	0.30 (0.58)	−0.34 (−0.99)	0.053
	5	−0.34 (−0.72)	−0.10 (−0.22)	−0.41 (−1.47)	0.000
	6	0.45 (0.71)	**−1.56**∗ (−3.06)	1.33 (1.19)	0.019
	7	0.16 (0.54)	0.26 (0.84)	−0.26 (−0.89)	0.017

Table 29
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). 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 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.

Maturity	Alt. model vs RW	MSE_U/MSE_R	Test statistic
$dy_{t+1}^{(1Y)}$	Dealer 1: OF^S,OF^M	0.978	**29.91***
	Dealer 4: OF^M,OF^L	0.996	**4.56 ***
	Dealer 5: OF^S,OF^M	0.996	**4.03***
$dy_{t+1}^{(2Y)}$	Dealer 1: OF^S,OF^M	0.981	**24.56***
	Dealer 4: OF^L	0.996	**7.10***
	Dealer 5: OF^M	0.996	**6.79***
$dy_{t+1}^{(3Y)}$	Dealer 1: OF^S,OF^M	0.985	**18.69***
	Dealer 4: OF^L	0.996	**7.09***
	Dealer 5: OF^S,OF^M	0.996	**6.26***
$dy_{t+1}^{(4Y)}$	Dealer 1: OF^S,OF^M	0.988	**14.36***
	Dealer 4: OF^L	0.992	**6.97***
	Dealer 5: OF^M	0.996	**4.23***
$dy_{t+1}^{(5Y)}$	Dealer 1: OF^S,OF^M	0.991	**14.29***
	Dealer 4: OF^L	0.996	**7.57***
	Dealer 5: OF^M	0.996	**4.20***
$dy_{t+1}^{(10Y)}$	Dealer 1: OF^M,OF^L	0.995	**5.07***
	Dealer 3: OF^M	1.000	0.29
	Dealer 4: OF^L	0.989	**13.23***
	Dealer 7 : OF^M,OF^L	1.005	-3.88

Table 30
Out-of-Sample predictions of monthly yield changes at dealer level

The table compares the out-of-sample predictive power of alternative order flow models to the random walk (RW). 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 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.

Maturity	Alt. model vs RW	MSE_U/MSE_R	Test statistic
$dy_{t+1}^{(1Y)}$	Dealer 1: OF^S,OF^M	0.885	**6.77***
	Dealer 3: OF^S,OF^M	0.916	**4.77***
	Dealer 4: OF^S	0.971	**1.58 ***
	Dealer 5: OF^M	0.962	**2.03***
$dy_{t+1}^{(2Y)}$	Dealer 1: OF^M	0.884	**6.80***
	Dealer 3: OF^S,OF^M	0.894	**6.15***
	Dealer 4: OF^S	0.960	**2.17***
	Dealer 5: OF^S	0.959	**2.25***
	Dealer 6: OF^M	0.995	0.24
$dy_{t+1}^{(3Y)}$	Dealer 1: OF^M	0.895	**6.09***
	Dealer 2: OF^S	1.028	-1.39
	Dealer 3: OF^S,OF^M	0.912	**5.03***
	Dealer 4: OF^S	0.957	**2.31***
	Dealer 5: OF^S	0.958	**2.26***
	Dealer 6: OF^M	0.996	0.21
$dy_{t+1}^{(4Y)}$	Dealer 1: OF^M	0.902	**5.67***
	Dealer 2: OF^S	1.011	-0.56
	Dealer 3: OF^S,OF^M	0.937	**3.49***
	Dealer 4: OF^S	0.955	**2.42***
	Dealer 6: OF^M	0.996	0.23
$dy_{t+1}^{(5Y)}$	Dealer 1: OF^M	0.906	**5.38***
	Dealer 2: OF^S	1.004	-0.23
	Dealer 4: OF^S	0.953	**2.54***
	Dealer 6: OF^M	0.995	0.26
$dy_{t+1}^{(10Y)}$	Dealer 1: OF^M	0.944	**3.07***
	Dealer 2: OF^S	1.031	-1.55
	Dealer 4: OF^S	0.938	**3.44***
	Dealer 6: OF^M	0.999	0.03

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. In periods when the curve increases, the order flow model predicts better, in periods when it decreases, the random walk give the best predictions.

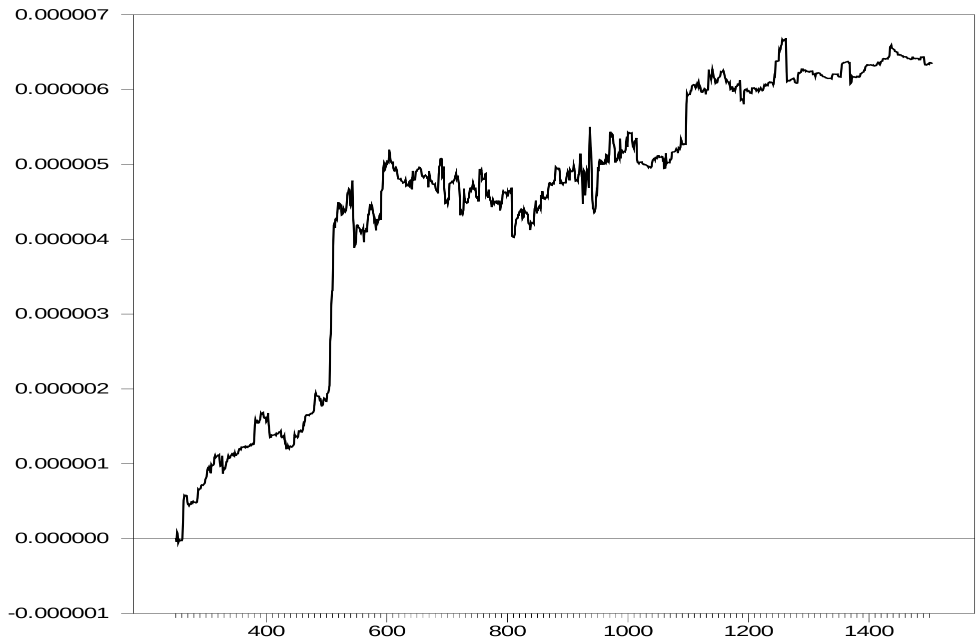

Figure 2: Predicting out-of-sample monthly 2 year yield changes using monthly short and medium term aggregate order flow. The curve illustrates the cumulative squared prediction errors of the random walk model minus the squared prediction errors of the order flow model. In periods when the curve increases, the order flow model predicts better, in periods when it decreases, the random walk give the best predictions.

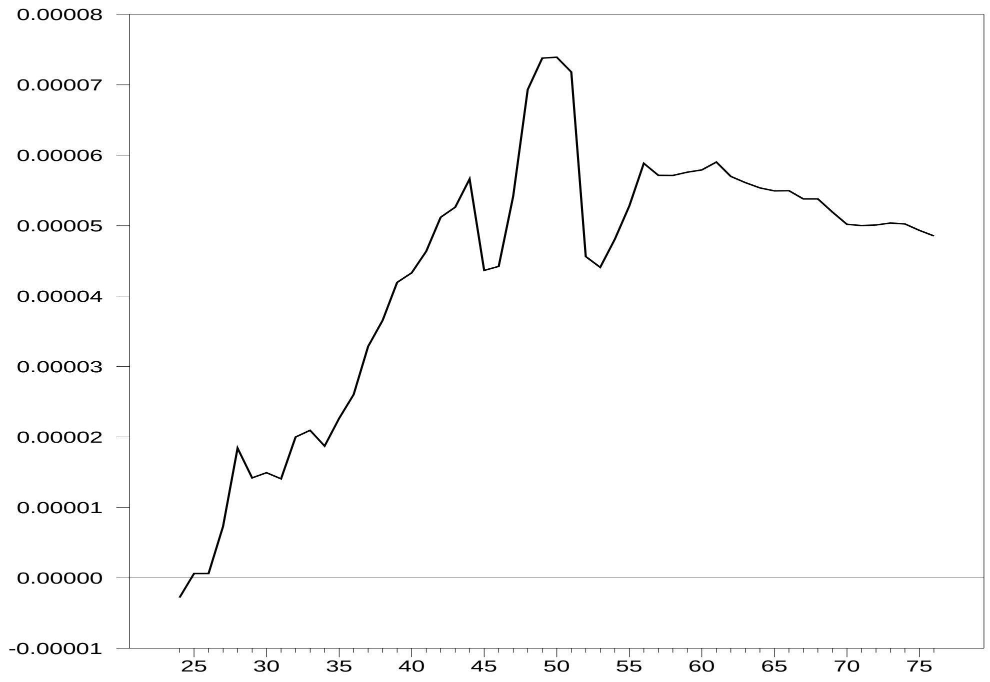

Figure 3: Predicting out-of-sample monthly changes in 2-year yields with the third principal component of forward rates. The curve illustrates the cumulative squared prediction errors of the random walk minus the squared prediction errors of the order flow model. In periods when the curve increases, the order flow model predicts better, in periods when it decreases, the random walk give the best predictions.

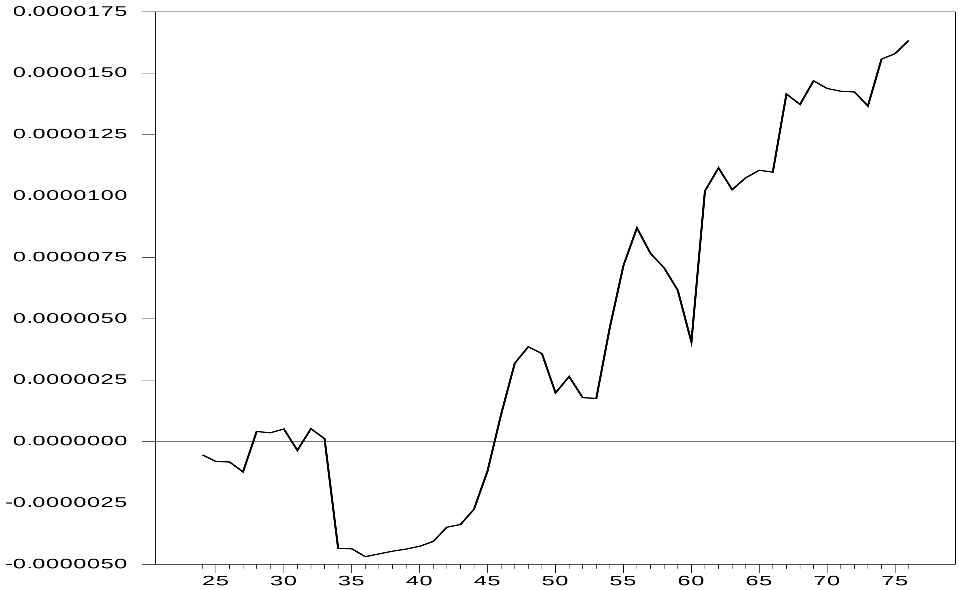

Figure 4: Predicting out-of-sample daily 3 year yield changes using the short and medium term interdealer order flow of Dealer 1 (black curve) and Dealer 2 (grey curve). The curves illustrate the cumulative squared prediction errors of the random walk minus the squared prediction errors of each order flow model. 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.

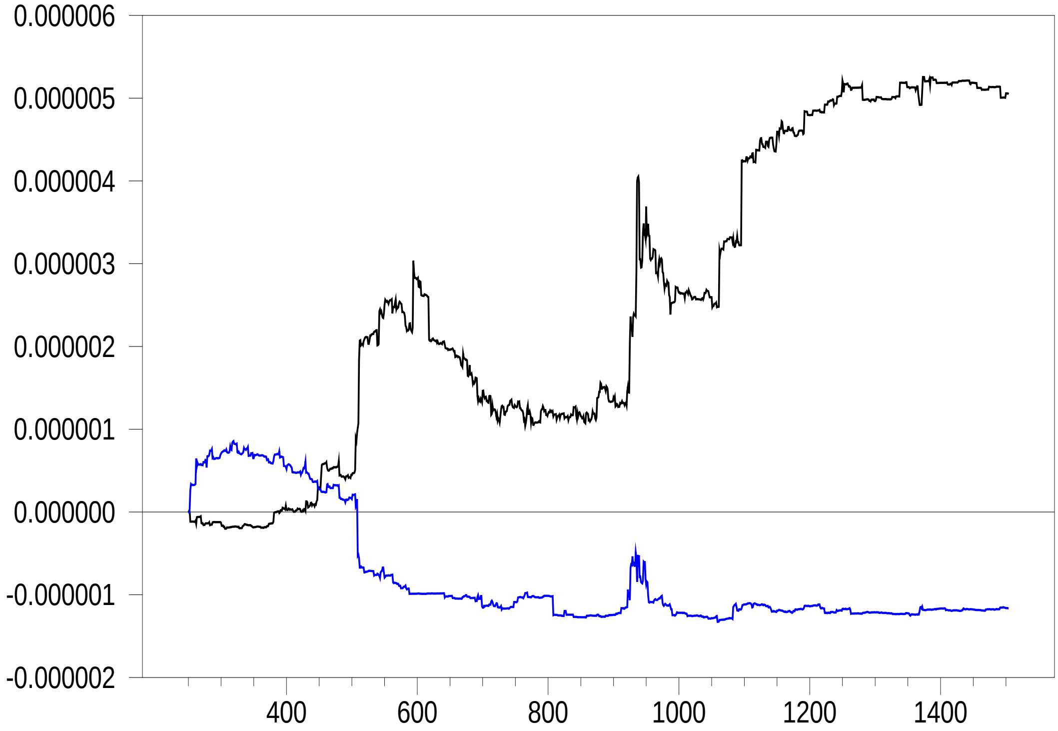

Figure 5: Predicting out-of-sample monthly 3 year yield changes using the medium term interdealer order flow of Dealer 1 (black curve) and the short term interdealer order flow of Dealer 2 (grey curve). The curves illustrate the cumulative squared prediction errors of the random walk minus the squared prediction errors of the order flow models. 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.