

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. The results show that order flow has significant forecasting ability, over and above the predictive power of forward rates, along the whole yield curve. The source of predictability in order flow is explored by using a new data set from the Norwegian government bond market, which includes both the customer and interdealer market, different trade categories and dealer identities. By dividing order flow according to trade type and individual dealer characteristics, the paper seeks to determine whether the source of predictability is customer trades or dealer skill and effort. The results suggest that dealer skill and effort in collecting private information, such as interpretations of macroeconomic news, liquidity conditions and investor risk appetite is an important source of predictability in interdealer order flow. Out-of-sample forecasts of daily and monthly yield changes confirm that models including order flow outperform the random walk and models based on forward rates only.

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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, especially for horizons up to 2 years. These results have supported the view that interest rates follow a "random walk", implying 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 yield changes. 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 is 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 news not yet incorporated into bond yields, can predict yield changes in the presence of forward rates.

Order flow, measured as the net buying pressure in the market, may contain private information about asset prices.¹ Lyons (2001) defines private information as information not known by all people 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 dispersed private information related to, for example, market liquidity, hedging activity and the perception of risk among market participants. In other words, order flow is a measure of fundamental and non-fundamental information held by economic agents trading in the market. Several market microstructure studies have documented a relationship between order flow and contemporaneous asset price changes. Evans and Lyons (2002), Hasbrouck (1991) and Brandt and Kavajecz (2004) show that order flow contains information about exchange rates, stock prices and bond yields, respectively. Valseth (2010) finds that dealers have heterogeneous contributions to price discovery in sovereign bond markets. Evans and Lyons (2005), in a study of the foreign exchange market, show that order flow also contains information about future asset prices. They find that order flow has predictive power for exchange rates, and 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 order flow as a new variable in a traditional term structure model. Second, it includes order flow based on trade type and individual dealers in the model in order to identify the source of predictability. The paper uses a new data set including both the interdealer market and the customer market in Norwegian government bonds. The data set, covering the period from September 1999 to September 2005, includes trade types and dealer identities. Order flow can thus be separated according to different characteristics. This enables the paper to address questions that cannot be addressed using other data sets. A commonly used data source is GovPX, which contains US Treasury interdealer trades, but does not include customer trades or dealer identities.² Other frequently used data sets contain

¹Order flow is in study defined as the number of buyer-initiated trades minus the number of seller-initiated trades during a day. A positive number indicates a net buying-pressure and vice versa.

²According 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

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.

One interesting question, so far unexplored empirically due to lack of data, is to investigate why interdealer order flow has predictive power. The information contained in interdealer order flow can be information the dealer has obtained from her customer trades or from using her skill and effort in interpreting available market information and extracting information from other dealers. Two possible sources of predictive power are thus customer trades and dealer skill and effort.³ The sources of predictability are related to the role of dealers in the price formation process in asset markets. Are dealers just passive intermediaries executing customer trades or are they actively seeking information? Do they exert skill and effort by extracting information from other traders and public sources, process this information and trade accordingly? If dealers are active, meaning that they are using effort to collect information relevant for future prices, the results in this paper should show that dealer skill and effort is an important source of predictability. If dealers are not exerting effort, but acting as passive intermediaries, the results of this investigation should show that customer trades are the main source of predictability.

The main results in this study show that aggregate interdealer order flow can predict yield changes along the whole yield curve and that the forecasting power of order flow is over and above the predictive power of forward rates. The results further show that dealers have different forecasting ability and that the best predictors do not appear to have customer order flow as their main source of predictability. Rather, the forecasting ability of individual dealers appears to be related to whether dealers are passive intermediaries or actively seeking information. When comparing one active and one passive dealer with access to the same amount of customer trades, only the active dealer has significant predictive power. This indicates that dealer skill and effort is a more important source of predictability in interdealer order flow than customer trades.

In order to investigate the main source of predictability in interdealer order flow, order flow is separated according to trade type and individual dealers. First, the source of predictability is explored by constructing order flow reflecting informed customer trades and order flow reflecting dealer trades independent of informed customer trades. Customer trades included in the category "delayed publication" are in this study assumed to be informed customer trades, as they are chosen by dealers to be made public only after a period of delay.⁴ If order flow based on informed customer trades predict yield changes, private information from informed customers appear to be a source of predictability. Second, the source of predictability is explored by comparing the predictive power of individual dealer order flow. If the predictive ability of the dealers varies, the characteristics of the best predictors are examined. Dealers are characterized by size, customer base and effort in collecting information. The size of a dealer is measured by her total market share in the customer and interdealer markets combined. The customer base is measured as her market share in the customer market. Effort is measured as a dealer's share of initiated interdealer trades relative to her customer trades. If a dealer with high effort predicts yield changes better than a dealer with low effort, but has comparable size and customer base, private information based on dealer effort

volume represents roughly 45 percent of the trading volume in the secondary market for Treasury securities.

³Anand and Subrahmanyam (2008) discuss whether intermediaries (dealers) are more informed than their clients (customers). Also Menkveld, Sarkar and van der Wel (2010) investigate the role of customers and intermediaries in the price discovery process.

⁴The period of delay was 2 hours until May 2002, and since then all delayed publication trades are made visible in the electronic trading system at 4 p.m.

appears to be a source of predictability.

The results in this paper document that models including order flow make better predictions than models including forward rates only. Term structure models including order flow also make better predictions than the random walk. Lagged interdealer order flow can forecast 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 of 4 -7 years, predicts a fall in the 3-year yield of 12 basis points the next day. An increase in monthly medium term order flow of one standard deviation, predicts a 29 basis point decrease in the 3-year yield in the following month. The fact that both daily and monthly interdealer order flow have predictive power indicates that 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 results further indicate that dealer skill and effort are an important source of predictability in interdealer order flow. Interdealer order flow that is orthogonal to delayed publication customer trades has greater predictive power than informed customer trades along the whole yield curve. This indicates that factors other than informed customer trades are important sources of predictability. Predictions based on individual dealer order flow support this conclusion, as the size of the customer base does not appear to determine whether a dealer has predictive ability or not. However, the order flow of dealers who exert effort, defined as dealers who actively trade with other dealers, has greater predictive power than the order flow of dealers who are passive intermediaries. Also, large dealers exerting effort have greater predictive power than small dealers exerting effort. These results suggest that the predictive power of dealers depends on dealer effort and skill in collecting and interpreting relevant information.

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 (2008).

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 as the reason for the yield changes. 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 significant and permanent impact on daily bond yield changes on news days as well as on no-news days.⁵ Valseth (2010) finds similar results from the Norwegian government bond market when including all news days and no-news days. Interdealer order flow explains more than a quarter of daily yield changes in Norwegian government bonds. She also finds that aggregate customer order flow contains little information on bond yields. 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 in-sample and out-of-sample predictions of daily and monthly yield changes.

Predictability based on microstructure models is documented in a recent study by Evans and Lyons (2005). They find that models including order flow in foreign exchange markets have significant out-of-sample forecasting power for exchange rates. 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 exchange 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 is addressing a different asset market. Second, it is using interdealer order flow instead of customer order flow. Third, it is employing a data set including types of trades and dealer identities, and can therefore investigate possible sources of predictability. Fourth, this paper attempts to reveal

⁵They 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.

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, and implies that forward rates are expected future spot rates and thus can predict future yield 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 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. All studies use monthly observations, Fama and Bliss (1987) 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 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 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 potentially 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 asset 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 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 Norwegian government bond market consists of four to six benchmark bonds, which have a remaining time to maturity of up to 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 bid and ask prices submitted by bond 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. Small trades are assumed to be uninformative as the average trade size is 35 million NOK. 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 are then aggregated into daily net order flow. Net order flow, referred to as order flow in this study, 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. These markets are described in the next subsection.

Order flow is divided into three maturity segments according to the remaining time to maturity of the bonds included. Short term order flow includes the order flow in bonds with a remaining time to maturity between 1 and 4 years, medium term order flow includes bonds with a remaining time to maturity between 4 and 7 years and long term order flow includes trades in bonds with a remaining time to maturity between 7 and 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

⁶Since 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.

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.

3.2 The secondary market for Norwegian government bonds

The secondary market for Norwegian government bonds is organized similarly to major government bond markets. A system of appointed primary dealers is managed by the Central Bank. Primary dealers have to be members of the OSE, and membership may be granted to Norwegian and foreign investment firms authorized to provide investment services in Norway or in their country of origin. The number of primary dealers has varied between 5 and 8 during the sample period. Typically, primary dealers are banks and brokerage firms. The primary dealers are obliged to provide firm bid and ask prices, with a maximum spread and for a minimum amount, for all benchmark bonds when the market is open. The bond market opening hours are 9 am - 4 pm.

While the participants in the primary market are mainly primary dealers, the participants in the secondary market also include other authorized bond dealers and non-dealers, referred to as customers. Thus, the secondary market can be divided into a customer market and an interdealer market. The customer market is the market between bond dealers and their customers. Customers may be institutional investors, commercial firms and individuals. Customers in general do not have access to the electronic trading system and have to execute their bond trades through dealers. The interdealer market comprises bond dealers who are connected to the OSE electronic trading system. In the interdealer market trades are agreed on both electronically and "over-the-counter".⁷

Dealers trade in both the customer market and the interdealer market. They may take risk in one market and off-load risk in the other market. In the customer market the dealers may compete for customer trades by offering favorable prices and good service. In the interdealer market, dealers may offer liquidity to other dealers and off-load risk incurred in the customer market.⁸ 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 where the buying and selling dealer are different 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 NOK. Interdealer trades are on average around 22 million NOK, and customer trades are on average around 36 million NOK. The share of electronic trading and the average electronic trade size has gradually increased since the inception of an electronic order book in 1999. Electronic trades and over-the-counter trades constitute roughly one half of the interdealer market each. 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

⁷"Over-the-counter" trades are agreed on over the phone or any communication systems other than the electronic order book.

⁸The primary dealer agreement requires that they provide continuous bid and ask prices.

over 250 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.

3.3 Descriptive statistics

To investigate the predictive power of forward rates, this study uses the first three principal components of forward rates. Tables 1a and 1b show the decomposition of forward rates into principal components. Table 1a presents the six factors extracted from the six 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 1b 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.⁹

Descriptive statistics for monthly data are presented in Table 2a for daily data and in Table 2b. Table 2a displays 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 2a 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 sales 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 "delayed publication" customer order flow, have means close to zero for all three maturities.

Finally, Table 2a 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. This factor

⁹Litterman and Scheinkman (1991) determines the common factors that have affected the Treasury returns and find that the variation in returns on all Treasury fixed income securities can be explained by three factors named level, steepness and curvature.

explains almost 93 percent of the variation in forward rates. The average value and the standard error of the forward spreads increase with the maturity of the forward rates, which is expected as the forward spread is defined as the forward rate minus a short term interest rate. This paper uses the one month rate as the short term interest rate.

Table 2b 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 up 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.¹⁰

Table 2c presents the correlations between the different predictive variables employed at the daily horizon. It appears that short, medium and long term interdealer order flow are positively correlated with a correlation around 20 percent. Short, medium and long term customer order flows based on delayed publication trades are also positively correlated. However, whereas the correlation between short and medium term order flow is 13 percent, the correlation of the short or medium term order flow with the long term customer order flow is only 2-3 percent.

Table 2d presents the correlations between the predictive variables at the monthly frequency. The correlation between short and medium term interdealer order flow is much higher at the monthly than at the daily frequency, with a positive correlation coefficient of 57 percent. However, the correlation between long term order flow and medium term order flow is lower. The correlation between long term order flow and short term order flow is about the same at the monthly horizon as at the daily horizon.

4 Theoretical background and econometric framework

4.1 Market microstructure

While traditional term structure models assume that asset prices instantaneously reflect all new information, market microstructure theory focuses on the process of price formation over time. According to 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 incorporated into prices through trading activity. Order flow contains private information that will gradually be incorporated into asset prices. Dealers observe the order flow, infer private information, update their expectations and set prices accordingly. Private information is defined by Lyons (2001) as information not known by all people that produces a better price forecast than public information alone. This implies that private information may include heterogeneous interpretations of public information.

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,

¹⁰The 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.

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 this variable has potential as a predictor of future yield changes.

Also, studies on predictability from other asset markets indicate that bond market order flow may have predictive ability. Evans and Lyons (2005) show that order flow is a predictor variable for exchange rate changes. They find that a model based on disaggregated customer order flow has higher predictive ability than a model based on aggregate customer order flow. In this paper, aggregate interdealer order flow, individual dealer interdealer order flow and delayed publication 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 effort and skill in obtaining private information. If dealers are passive intermediaries, informed customer trades are likely to be their main source of information. Passive dealers will just pass on customer trades to the interdealer market in order to off-load risk. If dealers are actively seeking private information, dealer effort and skill is likely to be the main source of information. Active dealers will exert effort and skill in processing relevant information. One example of dealer skill and effort 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 from other dealers. By observing the trading and pricing behavior of other dealers, a dealer can obtain information about the future direction of bond prices.

The private information held by bond dealers will be reflected in their order flow and gradually become impounded into bond prices through the mechanisms described in Bayesian learning models.¹¹

4.2 The expectations hypothesis and the classical term structure model

The analysis in this paper is based on a simple term structure model built 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,

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

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

¹¹See for example O'Hara (1995).

equation (1) and expressing the yield as a function of price, equation (1) becomes

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

where $y^{(N)}$ is the log yield and $p^{(N)}$ is the log price of a zero coupon bond with N years to maturity. The return of a zero-coupon bond is

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

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,

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

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,

$$f_t^{(N \rightarrow N+1)} = E_t(y_{t+N}^{(1)}) + \textit{Risk Premium}, \quad (5)$$

where $f_t^{(N \rightarrow N+1)}$ 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,

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

where $E_t(r_{t+1}^{(N)})$ is the one-period return at time t+1 expected at time t. In its pure form there is no risk premium included in the expectations model, but the model can be modified to include a constant term premium. By rearranging equation (6) it appears that the theoretical risk premium equals the expected excess return

$$E_t(\textit{exr}_{t+1}^N) = E_t(r_{t+1}^{(N)}) - y_t^{(1)}, \quad (7)$$

where $E_t(\textit{exr}_{t+1}^N)$ 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 has 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 $N \text{ years} - 1 \text{ day} \approx N \text{ years}$ and $N \text{ years} - 1 \text{ month} \approx N \text{ years}$. Yield changes and bond returns are calculated according to

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

and

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

where $dy_{t+1}^{(N \text{ years})}$ 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,

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

Equation (10) states actual excess bond return at time t+1. 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

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

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

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

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 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), includes lagged order flow only. The last two models, d) and e), include order flow in the term structure models. Both the Fama-Bliss maturity dependent forward spread defined in equation (11) and forward rates are used as predictor

variables.¹² However, instead of using the Cochrane-Piazzesi linear combination of forward rates, 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 forward spread as the only predictor variable,

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

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

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

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,

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

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,

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

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

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 are better predictors of bond excess returns than of yield changes, the predictive power of order flow on excess returns is also explored. By employing the same five models to predict excess returns, this paper investigates whether there is a predictive asymmetry in order flow similar to what is found for forward rates. All regression models, presented in equations (13) to (17), are thus performed twice on the daily forecast horizon: first on yield changes and then on excess returns.

4.5 Monthly forecasting models

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 ob-

¹²All 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. The results of the predictive regressions are presented in the tables in Appendix 1.

servations, the monthly analysis is based on 75 non-overlapping monthly observations.¹³ Monthly order flow is constructed by aggregating daily order flow over 20 day periods.

The first model, model f), uses the Fama-Bliss maturity dependent forward spread as the only predictor variable. This model is identical to model a) presented in equation (13) in the previous section. The second model, model g), uses all forward rates, expressed as the first three principal components of forward rates, as predictive variables. The principal components are based on monthly forward rates. This model is identical to model b) presented in equation (14) in the previous section. The third model, model h), includes monthly order flow only. This model is identical to model c) presented in equation (15) in the previous section. The fourth model, model i), is a term structure model based on the maturity dependent forward spread that includes order flow. This model is identical to model d) presented in equation (16) in the previous section. Finally the fifth model, model j), includes monthly order flow at the short, medium and long end of the yield curve and traditional term structure variables represented by the three first principal components of forward rates. This model is identical to model e) presented in equation (17) in the previous section.

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 3a 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 for any maturity except for the 1-year yield. Also model b), which includes the first three principal components of forward rates, has little predictive power. The first and second principal components have no significant coefficients for yields of any maturity. The third principal component of forward rates is significant in the 10-year yield model only.

Model c) is a pure order flow model. Daily yield changes are predicted with the lagged order flow of short, medium and long term bonds. The table shows that 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^2 s varying from 2.9 to 1.0

¹³Recent 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.

percent. Also, 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 3.7 trades today will, all other equal, reduce the 3-year yield by 12 basis points tomorrow. However, in the predictive regression 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 3a 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^2 s 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 3b 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 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^2 s 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 are significant predictors of excess returns, and that the predictive power of order flow on excess returns and yield changes is of similar magnitude with adjusted R^2 s varying from 3.0 to 1.1 percent.. In line with the results for yield changes, medium term order flow has the most significant predictive power both economically and statistically on excess bond returns. The sign, however, is opposite that of yield changes, due to the 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, which include forward rates *or* order flow, in predicting bond excess returns. The adjusted R^2 s 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 presented in table 3a.

5.2 Monthly predictions

Table 4a displays the results of the in-sample predictions of monthly yield changes. The monthly predictions are based on models f) to j) presented in subsection 4.5 using non-overlapping monthly

data.¹⁴ The results of model f), which has the forward spread as the only predictive variable, reveal the same pattern as the daily model. For all yields except the 1-year yield, the forward spread has no significant predictive power. Model g), which includes the first three principal components of forward rates, has increased forecasting power at the monthly horizon. The third principal component is statistically significant across all yields except for the 10-year yield.

Model h), which includes monthly order flow only, shows that order flow explains a substantial part of monthly yield changes, with an adjusted R^2 of between 6 and 17 percent across all yields. These in-sample results are in line with Evans and Lyons (2005) who find that the predictive power of lagged order flow increases with the horizon when looking at exchange 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.

There are some differences between the predictive power of order flow of different maturities at the daily and monthly horizons. Medium term monthly order flow has significant forecasting power across all yields, whereas long term monthly order flow has no significant coefficients along the yield curve. Short term order flow has predictive power for 1 to 3 year yields, but the economic significance of short term order flow is lower than that of medium term order flow, except for the 1-year yield. An increase in medium term order flow of one standard deviation will decrease the yield of the 3-year bond with 28 basis points in the following month. Model i), which includes both the forward spread and order flow, does not improve the forecasting power relative to model h), 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 j), combining the principal components of forward rates and order flow, outperforms both model g) and model h) across all yields except for the 10-year yield, with adjusted R^2 s increasing from 11.5 percent for the 5-year yield to 18.4 percent for the 1-year yield.

Table 4b presents the in-sample predictions for monthly bond excess returns. The results of model f) and model g) 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 g) 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 term 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 imply

¹⁴Because 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.

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 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 (RW) model can be written as

$$dy_{t+1}^{(N \text{ years})} = c + v_{t+1}, \quad (18)$$

where $dy_{t+1}^{(N \text{ years})}$ is the one period N year yield change, c is a constant and v_{t+1} is the error term. Equation (23) 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

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

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 (24) 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.¹⁵ Critical values of this non-standard test are provided in Clarck 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

¹⁵Since 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.

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 5a and 5b 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 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 5a shows the models predicting daily yield changes. The first column lists the maturity of the bond. 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 5a 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 the order flow model is tested. 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. 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 5b 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 order flow model and the RW model. When comparing the MSE-ratios and values of the test statistics in table 5b to those in table 5a, order flow appears to have roughly the same forecasting power for yield changes and excess returns.

6.2 Monthly predictions

Table 6a and 6b 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 6a 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 6b, 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 contain 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.¹⁶ The second source is private information held by dealers due to their skill and effort in collecting relevant information. In order to investigate whether the source of predictability is customer trades or dealer skill and effort, 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 a source of predictability. If interdealer order flow unrelated to informed customer order flow predict yield changes, we infer that dealer skill and effort may be a source of predictability.¹⁷

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 3.2, 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 part of interdealer order flow unrelated to delayed publication customer order flow is assumed to reflect trades based on dealer skill and effort. To derive the part of interdealer order flow orthogonal to informed customer trades, the following regression is employed;

$$OF_t = c + \psi HCOF_t + v_t, \quad (20)$$

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), v_t , are subsequently renamed,

$$v_t = resOF_t, \quad (21)$$

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. Interdealer order flow in each maturity group can now be expressed as

$$OF_t = HCOF_t + resOF_t, \quad (22)$$

illustrating that interdealer order flow can be decomposed into delayed publication customer order flow and orthogonalized interdealer order flow. Equation (22) says that interdealer order flow consists of one part reflecting informed customer trades and another part reflecting trades based on dealer skill and effort. To test for the source of predictability in interdealer order flow, the

¹⁶It 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 eventually reflect informed customer trades.

¹⁷Interdealer order flow orthogonal to informed customer trades may also contain interdealer trades based on uninformed customer trades and other uninformative/liquidity trades. However, it is assumed that these type of trades are about 50 percent buyer initiated and 50 percent seller initiated, and thus offset each other over time. Trades based on dealer skill and effort will then be reflected in the orthogonalized interdealer order flow.

following three models are run for each maturity,

$$dy_{t+1}^{(Nyears)} = \gamma_0 + \mathbf{\Lambda F}_t + \gamma_4 HCOF_t^S + \gamma_5 HCOF_t^M + \gamma_6 HCOF_t^L + \varepsilon_{t+1}, \quad (23)$$

$$dy_{t+1}^{(Nyears)} = \varphi_0 + \mathbf{\Lambda F}_t + \varphi_4 resOF_t^S + \varphi_5 resOF_t^M + \varphi_6 resOF_t^L + \varepsilon_{t+1}, \quad (24)$$

$$dy_{t+1}^{(Nyears)} = \beta_0 + \mathbf{\Lambda F}_t + \sum_{i=S}^L \gamma_i HCOF_t^i + \sum_{i=S}^L \varphi_i resOF_t^i + \varepsilon_{t+1}, \quad (25)$$

where $i = S, M, L$ indicates short term, medium term and long term maturity respectively. The model presented in equation (28) tests the predictive power of informed customer trades. This model is called model k) for daily forecasts and model n) for 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, $\mathbf{F}_t(F1_t, F2_t \text{ and } F3_t)$, and a constant. The model presented in equation (29) tests the predictive power of trades based on dealer skill and effort. It is called model l) for daily forecasts and model o) for monthly forecasts. In addition to the orthogonal part of interdealer order flow, $resOF_t^S$, $resOF_t^M$ and $resOF_t^L$, the model includes the three principal components of forward rates, and a constant.

The model shown in equation (30) includes both parts of interdealer order flow; the proxy for informed customer trades and the proxy for trades based on dealer skill and effort, as well as forward rates. By substituting equation (27) into equation (17), both delayed publication customer order flow of short, medium and long term maturity and the orthogonal part of interdealer order flow of the same maturity groups are included. This model is referred to as model m) for daily forecasts and model p) for 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 3c 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 the main 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 3d displays the results for predictions of daily excess returns. The results are in line with the results for daily yield changes.

Table 4c 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 4d 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 5c and 5d 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 and effort, *resOF*, are compared to the random walk.

Table 5c 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 predictability. Table 5d shows that the results of the out-of-sample predictions of daily excess returns are in line with the results in table 5c. 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 6c and 6d 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.¹⁸ For the 10 year bond none of the alternative models can beat the RW. Table 6d 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 orthogonal interdealer order flow outperforms the other models both in-sample and out-of-sample for maturities up to 5 years. This suggests that private information due to dealer skill and effort 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 source of predictive power is private information from informed customers or from dealer skill and effort, individual dealers are

¹⁸The graph is not included in the paper, but is available upon request.

characterized according to the size of their customer base and a measure reflecting dealer effort. If the interdealer order flow of dealers with a large customer base has predictive power, we infer that private information from informed customers is an important source of predictability. If the order flow of dealers exerting effort by actively trading with other dealers has predictive power, we infer that private information gained from dealer skill and effort is an important source of predictability.

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.¹⁹ 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 and their effort to collect information. 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. Effort is measured as the value of a dealer's initiated interdealer trades relative to the value of her customer trades. This ratio may indicate whether a dealer is actively collecting information. A dealer initiating a trade is seen as impatient as she chooses to accept the current bid or offer price in order to make sure that the transaction takes place immediately.²⁰ If a dealer is exerting effort to obtain information about future price movements, she is likely to be impatient when she has received private information. She may thus 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 is exerting effort. Conversely, a low share of initiated interdealer trades may indicate that a dealer is passive and not exerting effort.

Table 7 presents the characteristics of the seven dealers. They are numbered according to size as shown in column 1. The size, measured as total market share of each dealer, is displayed in the second column. There are four large dealers, with a total government bond market share ranging from 17 to 24 percent, constituting 85 percent of the government bond market. The remaining three dealers are small, with a total market share of 15 percent. The third column shows the size of each dealer's customer base as reflected in their market share in the customer market. The four large dealers also have the largest customer bases. If customer trades are the main source of predictability, these four dealers should be the best predictors, especially dealer 1 and dealer 2 with market share of 1/4 each.

The fourth column of table 7 displays the measure of dealer effort. The share of initiated interdealer trades relative to customer trades varies substantially between dealers. Among the four large dealers, the initiated interdealer trades over total customer trades varies between 19 and 42 percent.²¹ This relatively low percentage is related to the fact that the average size of customer trades is larger than the average size of interdealer trades. If dealer skill and effort is the main source of predictability, one would expect dealers with a high ratio to predict better than dealers with a low ratio. However, only one dealer differs from the others by having a very low share. This is dealer 2, who has a share of only 19 percent while the others have a share around 30 percent or

¹⁹The 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.

²⁰Correspondingly, 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.

²¹One very small dealer has a ratio of more than 400 percent indicating a very small customer base and a lot of proprietary interdealer trading.

higher. Compared to her customer base, the value of dealer 2's initiated interdealer trades is low, indicating that she is a passive dealer.

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,

$$dy_{t+1}^{(N \text{ years})} = \beta_0 + \mathbf{\Lambda} \mathbf{F}_t + \beta_3 OF_{D^i,t}^S + \beta_4^s OF_{D^i,t}^M + \beta_5^s OF_{D^i,t}^L + \varepsilon_{t+1}, \quad (26)$$

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 (31), 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 tables 8 to 11. 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 8a and 8b display the results for daily yield changes. Table 8a includes 1 to 3 year yield changes and Table 8b 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 is the second best predictor. The predictive power of Dealer 4 is due to long term order flow and the R^2 s vary between 0.6 and 1.4 percent at the daily horizon. The medium term order flow of Dealer 5 has predictive power for 1 to 4 year yield changes. 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 their R^2 s vary between 0.5 and 0.9 percent. These results indicate that dealers possess heterogeneous private information in their daily order flow.

Tables 9a and 9b display the results for monthly yield changes. Table 9a include 1 to 3 year yield changes and Table 9b 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 for 1 to 10 year yield changes, measured by R^2 , varies from 11.9 to 4.7 percent at the monthly horizon. 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^2 s 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 possess heterogeneous private information in their monthly order flow as well.

Table 10 and table 11 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 10 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 4 displays the Goyal and Welch (2008) metric for comparing the out-of-sample predictive power of Dealer 1's interdealer order flow to the RW for daily 3 year yield changes. The increase in the curve illustrates that the order flow model performs better, while the fall in the curve illustrates that the RW performs better. The metric displays an upward sloping curve over the period as a whole which means that the Dealer 1 order flow model outperforms the RW.

Table 11 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 flow of the other dealers have no predictive power at the monthly horizon, except for Dealer 5 who can forecast 1 to 3 year yield changes with short term order flow. Figure 5 illustrates that the monthly order flow of Dealer 1 clearly outperforms the RW for monthly 3-year yield changes.

The results in this section document that only two out of seven dealers have significant forecasting ability for all yield changes at both the daily and monthly horizon. These dealers, Dealer 1 and Dealer 4, are large dealers with a total market share of 24 and 17 percent respectively. They exert effort, measured as the share of their interdealer trades relative to their customer trades, of around 30 percent which is close to average.

Two dealers have partial 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. With a total market share of 21 percent and a customer market share of 19 percent Dealer 3 exerts effort above average. Dealer 5, who has a total market share of 9 percent and a customer market share of 9 percent indicating an average effort, 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.

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 exerts little effort, with a share of interdealer trades relative to customer trades of 19 percent, indicating that she is a passive dealer. From Table 7 we see 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, there must be something else than customer trades that are the main source of predictability in interdealer order flow. From Table 7 we see that their effort differs. Dealer 1 appears to be an active dealer with high trading activity in the interdealer market whereas Dealer 2 appears to be a passive dealer with relatively low activity in the interdealer market. This indicates that dealer skill and effort is an important source of predictability in interdealer order flow.

Other factors like customer types may also influence the predictability of individual interdealer order flow. If customers are heterogeneous, the information in customer trades will depend on the type of customer, and not the size of the customer base alone. Also, a dealer's skill and effort in identifying her informed customers may matter for the predictability of her interdealer order flow.

The results in this section point to another source of predictability than customer trades. In all, the findings in this and the previous section indicate that dealers with predictive power possess private information additional to the information in their own customer trades. The forecasting ability of individual dealers appears to be related to whether dealers are passive intermediaries or actively seeking information. Private information due to dealer skill and effort may thus be an important source of predictability in interdealer order flow.

9 Conclusion

The main contribution of this paper is to include bond market order flow as a predictive variable in traditional term structure models. Term structure models include only information that can be extracted from the current yield curve, like forward rates, yield spreads and common yield factors. These models have been shown to produce poor forecasts of yield changes, especially at short horizons. Recent studies indicate that information beyond that contained in the current yield curve matters for future changes in bond yields and bond returns. Ludvigson and Ng (2009) find predictable variation in bond returns related to macroeconomic factors independent of forward rates. Andersen and Benzoni (2010) find systematic factors in yield volatility that is unrelated to the current term structure. The results in this paper support these findings by documenting that lagged order flow has significant forecasting ability for yield changes, beyond the predictive power of forward rates.

The predictive power of order flow arises because the price formation process, in which asset prices adjust to full information prices, do not occur instantaneously, but evolves in markets over time. Order flow will thus contain information that is not yet incorporated into the yield curve. Daily order flow predicts daily changes, while monthly order flow predicts monthly changes in yields, suggesting that the time it takes for information to become impounded into bond prices may vary depending on the type of information. Interdealer order flow reflects private information, including interpretations of macroeconomic news and dispersed information about for example hedging demands, liquidity conditions or changes in investor risk aversion.

Another important contribution of this paper is to investigate why interdealer order flow has predictive power. A new data set enables the search for the source of predictability by analyzing order flow based on different trade types and on individual dealers. Of two dealers with the same size customer base, only one can predict future yield changes, indicating that customer trades is not the main source of predictability. Dealers who exert effort by being active in the interdealer market appear to be the best predictors. This indicates that some other factor, which could be

dealer skill and effort, is an important source of predictability in order flow. Different shares of informed customers may also explain some of the differences between dealers.

This paper also finds that order flow predicts excess returns. The results confirm the findings of Fama and Bliss (1987) that forward rates are better predictors for bond excess returns than for yield changes. However, order flow has roughly the same predictive power for both excess returns and yield changes while controlling for the effect of forward rates. This indicates that order flow predicts risk premia over and above the risk premia predicted by forward rates.

As a robustness check, out-of-sample predictions based on order flow are compared to the random walk, and the order flow model clearly outperforms the random walk for all maturities. Finally, this paper documents that the predictive power of order flow is robust to possible bias due to overlapping observations used in previous studies. The monthly forecasts have been performed on both overlapping and non-overlapping data, and the results are well aligned.

Although the Norwegian government bond market appears to work the same way as major government bond markets, an interesting extension of this study would be to explore the predictive power of aggregate interdealer order flow in the US and European sovereign bond markets.

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Table 1a
Principal components analysis of forward rates

The table displays the principal components of the one-month forward rates 1 to 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)
<i>F1</i>	5.569	0.928	0.928	0.997
<i>F2</i>	0.398	0.066	0.994	0.991
<i>F3</i>	0.030	0.005	0.999	0.892
<i>F4</i>	0.004	0.001	1.000	0.893
<i>F5</i>	0.000	0.000	1.000	0.881
<i>F6</i>	0.000	0.000	1.000	0.876

Table 1b
Loadings of principal components of forward rates

The table presents the loadings of the first three principal components on the 6 forward rates. The first 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).

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

Table 2a
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 2b
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
OFL	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 2c
Unconditional correlations daily data

The table presents the unconditional correlations of the various predictive variables on a daily basis.

	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 2d
Unconditional correlations monthly data

The table presents the unconditional correlations of the various variables on a monthly basis.

	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 3a
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	0.58* (3.02)						0.008	
	b		0.00 (0.53)	0.00 (1.51)	-0.01 (-0.64)			0.001	
	c					-0.09* (-2.05)	-0.13* (-3.86)	-0.05 (-1.54)	0.029
	d	0.54* (2.79)				-0.08 (-1.78)	-0.13* (-3.94)	-0.06 (-1.86)	0.036
	e		0.00 (0.05)	0.00 (1.49)	-0.00 (-0.28)	-0.09* (-1.97)	-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					-0.09 (-1.74)	-0.13* (-2.98)	-0.05 (-1.62)	0.020
	d	0.11 (0.94)				-0.09 (-1.71)	-0.13* (-2.93)	-0.06 (-1.64)	0.019
	e		-0.00 (-0.56)	0.00 (0.60)	0.01 (0.76)	-0.09 (-1.76)	-0.13* (-2.95)	-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)	-0.12* (-2.75)	-0.05 (-1.32)	0.014
	d	0.02 (0.25)				-0.07 (-1.31)	-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)	-0.12* (-2.53)	-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)	-0.12* (-2.33)	-0.05 (-1.77)	0.011
	d	-0.00 (-0.02)				-0.04 (-0.87)	-0.12* (-2.33)	-0.05 (-1.75)	0.011
	e		-0.00 (-0.65)	0.00 (0.61)	0.02 (1.87)	-0.05 (-0.97)	-0.12* (-2.33)	-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)	-0.11* (-2.20)	-0.06* (-2.17)	0.010
	d	-0.01 (-0.18)				-0.02 (-0.46)	-0.11* (-2.21)	-0.06* (-2.14)	0.010
	e		-0.00 (-0.57)	0.00 (0.82)	0.01 (1.75)	-0.02 (-0.55)	-0.11* (-2.20)	-0.07* (-2.40)	0.012
$dy_{t+1}^{(10 y)}$	a	-0.07 (-1.00)						0.000	
	b		0.00 (0.04)	0.00 (1.68)	-0.02 (1.90)			0.003	
	c					0.03 (0.74)	-0.06 (-1.54)	-0.11* (-4.01)	0.013
	d	-0.19 (-1.21)				0.02 (0.67)	-0.06 (-1.50)	-0.10* (-4.15)	0.013
	e		-0.00 (-0.25)	0.00 (1.86)	-0.01 (-1.85)	0.03 (0.88)	-0.06 (-1.45)	-0.11* (-4.12)	0.016

Table 3b
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		-0.00* (-8.33)	-0.01* (-4.32)	-0.00 (-0.25)				0.053
	c					0.10* (2.19)	0.12* (3.45)	0.07* (2.14)	0.030
	d	0.40 (1.76)				0.10* (2.27)	0.12* (3.73)	0.05 (1.68)	0.034
	e		-0.00* (-7.92)	-0.01* (-4.52)	-0.00 (-0.64)	0.07 (1.70)	0.12* (3.56)	0.06 (1.92)	0.078
$exr_{t+1}^{(2 y)}$	a	0.53* (2.24)							0.003
	b		-0.00* (-3.41)	-0.01 (-1.83)	-0.01 (-0.83)				0.007
	c					0.18 (1.80)	0.24* (2.82)	0.12 (1.92)	0.020
	d	0.54* (2.38)				0.18 (1.86)	0.25* (2.95)	0.11 (1.61)	0.023
	e		-0.00* (-3.13)	-0.01 (-1.87)	-0.02 (-1.19)	0.16 (1.63)	0.24* (2.84)	0.12 (1.90)	0.026
$exr_{t+1}^{(3 y)}$	a	0.56* (2.05)							0.002
	b		-0.00* (-2.02)	-0.01 (-1.30)	-0.04 (-1.59)				0.004
	c					0.19 (1.35)	0.35* (2.45)	0.16 (1.79)	0.014
	d	0.55* (2.13)				0.19 (1.36)	0.36* (2.52)	0.15 (1.58)	0.016
	e		-0.00 (-1.75)	-0.01 (-1.31)	-0.05 (-1.88)	0.19 (1.29)	0.35* (2.47)	0.17 (1.86)	0.018
$exr_{t+1}^{(4 y)}$	a	0.59 (1.84)							0.002
	b		-0.00 (-1.45)	-0.01 (-1.23)	-0.06 (-1.81)				0.003
	c					0.16 (0.89)	0.43* (2.26)	0.22 (1.95)	0.011
	d	0.56 (1.86)				0.16 (0.88)	0.44* (2.32)	0.21 (1.79)	0.013
	e		-0.00 (-1.20)	-0.01 (-1.25)	-0.07* (-2.08)	0.16 (0.88)	0.43* (2.28)	0.23* (2.08)	0.015
$exr_{t+1}^{(5 y)}$	a	0.63 (1.71)							0.001
	b		-0.00 (-1.18)	-0.01 (-1.30)	-0.07 (-1.65)				0.002
	c					0.10 (0.48)	0.50* (2.14)	0.31* (2.32)	0.011
	d	0.59 (1.68)				0.10 (0.47)	0.51* (2.20)	0.30* (2.18)	0.012
	e		-0.00 (-0.94)	-0.01 (-1.35)	-0.07 (-1.92)	0.10 (-0.63)	0.50* (2.16)	0.33* (2.48)	0.013
$exr_{t+1}^{(10 y)}$	a	1.17 (1.75)							0.002
	b		-0.00 (-0.77)	-0.03 (1.96)	0.15 (1.81)				0.004
	c					-0.24 (-0.71)	0.59 (1.51)	1.04* (4.07)	0.013
	d	1.01 (1.57)				-0.25 (-0.74)	0.61 (1.55)	1.00* (3.98)	0.015
	e		-0.003 (-0.53)	-0.04* (-2.15)	0.13 (1.75)	-0.31 (-0.92)	0.57 (1.44)	1.03* (4.15)	0.017

Table 3c

In-sample predictions of daily yield changes based on delayed publication 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.

	<i>model</i>	$HCOF_t^S$	$resOF_t^S$	$HCOF_t^M$	$resOF_t^M$	$HCOF_t^L$	$resOF_t^L$	<i>Adj.R</i> ²
dy_{t+1}^{1y}	<i>k</i>	-0.06 (-1.31)		-0.07 (-1.38)		-0.03 (-0.57)		0.003
	<i>l</i>		-0.08 (-1.96)		-0.12* (-3.47)		-0.05 (-1.49)	0.026
	<i>m</i>	-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}	<i>k</i>	-0.06 (-1.24)		-0.10 (-1.89)		-0.07 (-1.22)		0.003
	<i>l</i>		-0.08 (-1.72)		-0.12* (-2.69)		-0.05 (-1.64)	0.016
	<i>m</i>	-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}	<i>k</i>	-0.04 (-0.80)		-0.12* (-2.13)		-0.08 (-1.25)		0.004
	<i>l</i>		-0.07 (-1.36)		-0.11* (-2.32)		-0.05 (-1.77)	0.013
	<i>m</i>	-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}	<i>k</i>	-0.02 (-0.44)		-0.12* (-2.19)		-0.08 (-1.32)		0.004
	<i>l</i>		-0.04 (-0.95)		-0.10* (-2.14)		-0.05* (-2.11)	0.011
	<i>m</i>	-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}	<i>k</i>	-0.01 (-0.17)		-0.12* (-2.16)		-0.09 (-1.48)		0.004
	<i>l</i>		-0.02 (-0.57)		-0.09* (-2.02)		-0.06* (-2.58)	0.010
	<i>m</i>	-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}	<i>k</i>	0.03 (0.70)		-0.08 (-1.57)		-0.12* (-2.47)		0.009
	<i>l</i>		0.03 (0.79)		-0.05 (-1.31)		-0.09* (-4.10)	0.014
	<i>m</i>	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 3d

In-sample predictions of daily excess returns based on delayed publication 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.

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

Table 4a

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

Table 4b

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 f), g), h), i) and j) 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.

	<i>model</i>	FS_t	$F1_t$	$F2_t$	$F3_t$	OF_t^S	OF_t^M	OF_t^L	$Adj.R^2$
$exr_{t+1}^{(1\ year)}$	<i>f</i>	6.60 (1.03)							0.011
	<i>g</i>		-0.07* (-6.12)	-0.15* (-3.39)	-0.29* (-3.17)				0.411
	<i>h</i>					0.39* (2.62)	0.10 (0.55)	0.02 (0.12)	0.124
	<i>i</i>	14.83* (2.85)				0.51* (4.05)	0.15 (1.08)	-0.12 (-0.91)	0.214
	<i>j</i>		-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
$exr_{t+1}^{(2\ years)}$	<i>f</i>	10.29 (1.69)							0.029
	<i>g</i>		-0.06* (-2.34)	-0.14 (-1.41)	-0.63* (-2.70)				0.109
	<i>h</i>					0.55* (2.32)	0.43 (1.42)	0.00 (0.00)	0.110
	<i>i</i>	14.25* (2.72)				0.61* (2.92)	0.52* (1.98)	-0.14 (-0.67)	0.175
	<i>j</i>		-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
$exr_{t+1}^{(3\ years)}$	<i>f</i>	10.87 (1.56)							0.023
	<i>g</i>		-0.05 (-1.37)	-0.16 (-1.10)	-0.96* (-2.66)				0.061
	<i>h</i>					0.63 (1.94)	0.70 (1.54)	0.02 (0.07)	0.085
	<i>i</i>	12.57* (2.02)				0.64* (2.15)	0.79 (1.91)	-0.11 (-0.35)	0.121
	<i>j</i>		-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
$exr_{t+1}^{(4\ years)}$	<i>f</i>	11.53 (1.44)							0.018
	<i>g</i>		-0.05 (-0.97)	-0.20 (-1.09)	-1.21* (-2.72)				0.049
	<i>h</i>					0.67 (1.66)	0.95 (1.59)	0.06 (0.15)	0.074
	<i>i</i>	12.29 (1.67)				0.65 (1.72)	1.04 (1.89)	-0.07 (-0.17)	0.097
	<i>j</i>		-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
$exr_{t+1}^{(5\ years)}$	<i>f</i>	12.58 (1.36)							0.017
	<i>g</i>		-0.05 (-0.78)	-0.25 (-1.18)	-1.36* (-2.74)				0.041
	<i>h</i>					0.69 (1.45)	1.20 (1.65)	0.10 (0.22)	0.070
	<i>i</i>	12.89 (1.50)				0.65 (1.44)	1.30 (1.92)	-0.03 (-0.06)	0.089
	<i>j</i>		-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
$exr_{t+1}^{(10\ years)}$	<i>f</i>	21.29 (1.35)							0.018
	<i>g</i>		-0.04 (-0.40)	-0.66 (-1.88)	-0.82 (-1.06)				0.005
	<i>h</i>					0.75 (0.82)	2.39 (1.72)	0.39 (0.44)	0.060
	<i>i</i>	21.14 (1.37)				0.66 (0.72)	2.55* (1.98)	0.17 (0.18)	0.078
	<i>j</i>		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 4c

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}	n	-0.08 (-0.53)		-0.41* (-2.15)		0.16 (1.02)		0.029
	o		-0.38* (-3.30)		-0.14 (-1.24)		0.12 (1.00)	0.146
	p	-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}	n	-0.08 (-0.67)		-0.39 (1.90)		0.00 (0.02)		0.021
	o		-0.34* (-2.93)		-0.21 (-1.42)		0.11 (0.90)	0.128
	p	-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}	n	-0.08 (-0.78)		-0.37 (-1.94)		-0.09 (-0.49)		0.038
	o		-0.30* (-2.62)		-0.20 (-1.35)		0.10 (0.83)	0.111
	p	-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}	n	-0.08 (-0.82)		-0.35* (-1.99)		-0.15 (-0.89)		0.053
	o		-0.25* (-2.39)		-0.19 (-1.34)		0.09 (0.79)	0.097
	p	-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}	n	-0.09 (-0.82)		-0.33* (-2.01)		-0.19 (-1.22)		0.063
	o		-0.22* (-2.18)		-0.19 (-1.35)		0.09 (0.74)	0.084
	p	-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}	n	-0.11 (-0.85)		-0.24 (-1.65)		-0.28* (-2.32)		0.069
	o		-0.12 (-1.23)		-0.17 (-1.33)		0.05 (0.50)	0.016
	p	-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 4d

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

Table 5a
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 $F2, F3$	0.986 1.000	16.45* 2.57*

Table 5b
Out-of-Sample predictions of excess returns 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
$exr_{t+1}^{(1Y)}$	OF^S, OF^M, OF^L	0.970	36.57*
	$F1, F2$	0.950	68.14*
$exr_{t+1}^{(2Y)}$	OF^S, OF^M, OF^L	0.982	23.36*
	$F1, F2$	0.998	1.92*
$exr_{t+1}^{(3Y)}$	OF^M, OF^L	0.989	13.90*
	$F1$	1.005	-5.57
$exr_{t+1}^{(4Y)}$	OF^M, OF^L	0.991	11.75*
	$F3$	0.998	2.18*
$exr_{t+1}^{(5Y)}$	OF^M, OF^L	0.991	11.57*
	$F3$	0.999	1.63*
$exr_{t+1}^{(10Y)}$	OF^L	0.987	17.06*
	$F2, F3$	0.998	2.99*

Table 5c
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*
$dy_{t+1}^{(2Y)}$	$resOF^S, resOF^M$ $HCOF^M$	0.985 1.00	19.01* 0.73
$dy_{t+1}^{(3Y)}$	$resOF^M, resOF^L$ $HCOF^M$	0.992 0.999	10.85* 1.20
$dy_{t+1}^{(4Y)}$	$resOF^M, resOF^L$ $HCOF^M$	0.993 0.999	8.90* 1.20
$dy_{t+1}^{(5Y)}$	$resOF^M, resOF^L$ $HCOF^M$	0.993 0.999	8.63* 0.85
$dy_{t+1}^{(10Y)}$	$resOF^L$ $HCOF^L$	0.989 0.998	13.57* 1.98*

Table 5d

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*
$exr_{t+1}^{(2Y)}$	$resOF^S, resOF^M, resOF^L$ $HCOF^M$	0.985 0.999	19.72* 0.87
$exr_{t+1}^{(3Y)}$	$resOF^M, resOF^L$ $HCOF^M$	0.991 0.999	11.07* 1.31
$exr_{t+1}^{(4Y)}$	$resOF^M, resOF^L$ $HCOF^M$	0.993 0.999	9.09* 1.20
$exr_{t+1}^{(5Y)}$	$resOF^M, resOF^L$ $HCOF^M$	0.993 0.999	8.84* 0.92
$exr_{t+1}^{(10Y)}$	$resOF^L$ $HCOF^L$	0.989 0.998	13.89* 2.43*

Table 6a
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 6b
Out-of-Sample predictions of monthly excess bond 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 6c

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 6d

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 7
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, effort in collecting information and the impact of their order flow in predicting yield changes. Size is measured as total market share, calculated as the gross value of customer trades and initiated interdealer trades by the dealer as a percentage of the total value of both markets combined. Customer base is measured as the market share in the customer market, calculated as dealer gross value of customer trades as a percentage of total customer trades. Dealer effort in collecting information is measured as the value of a dealer's initiated interdealer trades over the value of her customer trades.

Dealer	Size	Customer base	Effort
	Total market share	Customer market share	$\frac{\textit{Interdealer trades}}{\textit{Customer trades}}$
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 8a
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	$OF_{i,t}^S$	$OF_{i,t}^M$	$OF_{i,t}^L$	$Adj.R^2$
dy_{t+1}^{1y}	1	-0.24* (-2.46)	-0.50* (-3.05)	-0.07 (-0.99)	0.023
	2	-0.09 (-0.65)	-0.10 (-1.23)	-0.10 (-1.10)	0.001
	3	-0.12 (-0.84)	-0.14 (-1.60)	-0.05 (-0.73)	0.003
	4	-0.06 (-0.50)	-0.17 (-1.73)	-0.20* (-2.24)	0.006
	5	-0.13 (-1.20)	-0.17* (-2.04)	-0.10 (-0.72)	0.005
	6	-0.24 (-1.22)	-0.10 (-0.52)	-0.18 (-0.85)	0.002
	7	-0.05 (-0.78)	-0.06 (-0.93)	-0.08 (-1.34)	0.002
dy_{t+1}^{2y}	1	-0.27* (-2.61)	-0.56* (-3.57)	-0.07 (-0.70)	0.018
	2	-0.17 (-1.02)	-0.06 (-0.48)	-0.11 (-1.04)	0.000
	3	-0.07 (-0.41)	-0.16 (-1.45)	-0.01 (-0.15)	0.000
	4	-0.10 (-0.75)	-0.17 (-1.52)	-0.28* (-2.89)	0.006
	5	-0.21 (-1.70)	-0.19 (-1.92)	-0.11 (-0.60)	0.004
	6	-0.08 (-0.33)	-0.09 (-0.46)	-0.07 (-0.31)	0.000
	7	0.01 (0.09)	0.03 (0.41)	-0.12 (-1.51)	0.000
dy_{t+1}^{3y}	1	-0.23* (-2.25)	-0.53* (-4.01)	-0.07 (-0.74)	0.015
	2	-0.17 (-1.07)	-0.05 (-0.37)	-0.08 (-0.72)	0.000
	3	-0.02 (-0.14)	-0.16 (-1.50)	0.01 (0.10)	0.000
	4	-0.10 (-0.70)	-0.18 (-1.52)	-0.29* (-3.12)	0.007
	5	-0.20 (-1.67)	-0.21* (-2.04)	-0.11 (-0.55)	0.005
	6	-0.00 (-0.02)	-0.09 (-0.54)	0.02 (0.09)	0.000
	7	0.02 (0.24)	0.08 (0.96)	-0.11 (-1.31)	0.000

Table 8b

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	$OF_{i,t}^S$	$OF_{i,t}^M$	$OF_{i,t}^L$	$Adj.R^2$
dy_{t+1}^{4y}	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_{t+1}^{5y}	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_{t+1}^{10y}	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 9a

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

Table 9b

In-sample predictions of monthly 4, 5 and 10 year yield changes based 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	$OF_{i,t}^S$	$OF_{i,t}^M$	$OF_{i,t}^L$	$Adj.R^2$
dy_{t+1}^{4y}	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_{t+1}^{5y}	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_{t+1}^{10y}	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 10
Out-of-Sample predictions of daily yield changes at dealer level

The table compares the out-of-sample predictive power of an alternative model based on 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.

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 11
Out-of-Sample predictions of monthly yield changes at dealer level

The table compares the out-of-sample predictive power of alternative models including order flow or forward rates to the random walk. 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.

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 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.

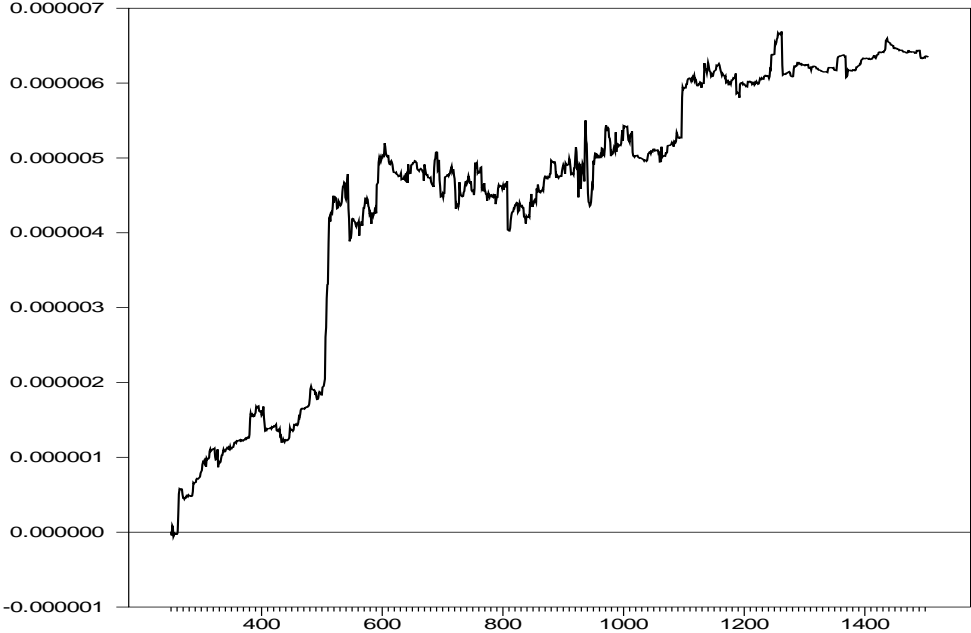


Figure 2: Predicting monthly 2 year yield changes using monthly short and medium term aggregate order flow. The curve illustrates the cumulative squared prediction errors of the random walk model minus the squared prediction errors of the order flow model. In periods when the curve increases, the order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

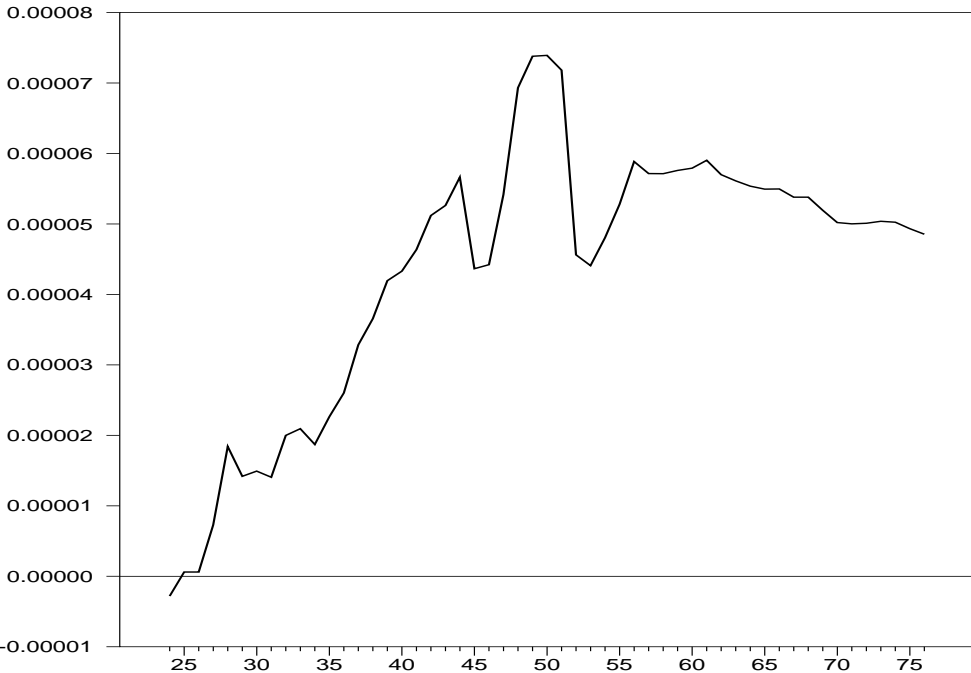


Figure 3: Predicting monthly changes in 2-year yields with the lagged third principal component of forward rates. The curve illustrates the cumulative squared prediction errors of the random walk minus the squared prediction errors of the order flow model. In periods when the curve increases, the order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

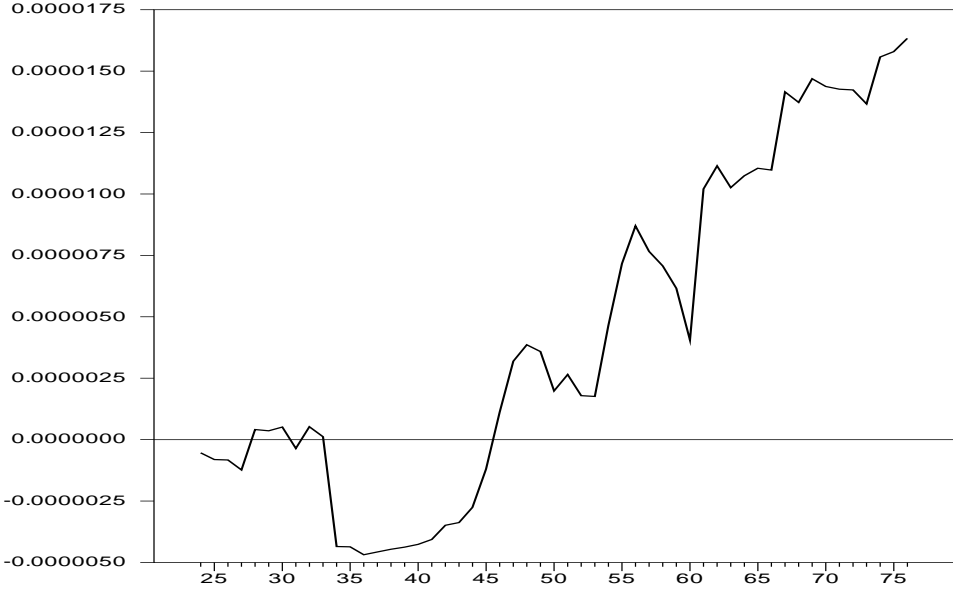


Figure 4: Predicting daily 3 year yield changes using the short and medium term order flow of dealer 1. The curve illustrates the cumulative squared prediction errors of the random walk minus the squared prediction errors of the order flow model. In periods when the curve increases, the order flow model predicts better, in periods when it decreases, the random walk give the best predictions.

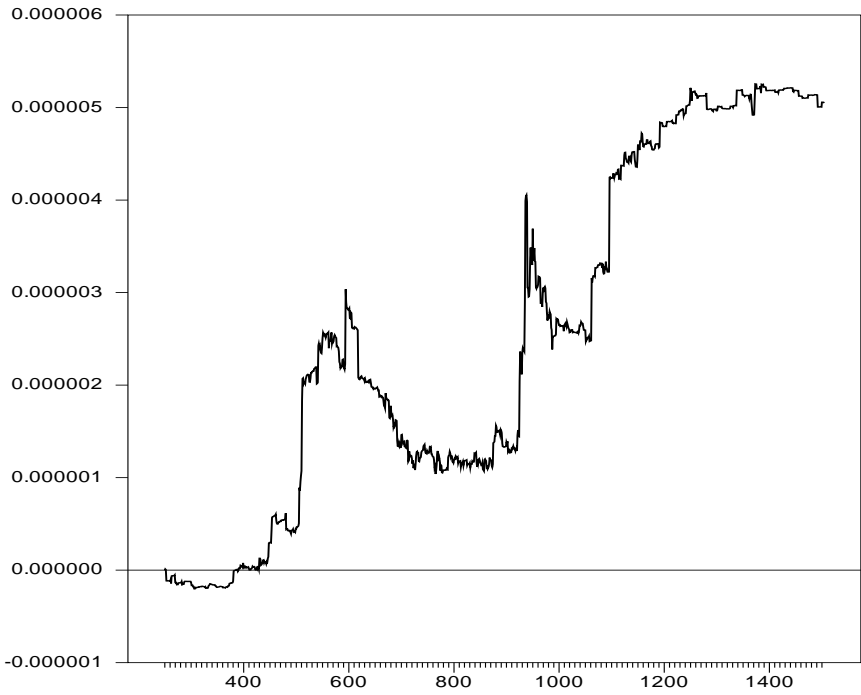


Figure 5: Predicting monthly changes in the 3 year yield with the medium term order flow of dealer 1. The curve illustrates the cumulative squared prediction errors of the random walk minus the squared prediction errors of the order flow model. In periods when the curve increases, the order flow model predicts better, in periods when it decreases, the random walk give the best predictions.

