NBER WORKING PAPER SERIES

PRICE DISCOVERY IN THE U.S. TREASURY MARKET: THE IMPACT OF ORDERFLOW AND LIQUIDITY ON THE YIELD CURVE

Michael W. Brandt
Kenneth A. Kavajecz

Working Paper 9529
http://www.nber.org/papers/w9529

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2003

We thank Alessandro Beber, Roger Edelen, Simon Gervais, Nick Souleles, Rob Stambaugh, Amir Yaron and seminar participants at the University of Colorado, University of Maryland, University of Pennsylvania and Morgan Stanley Dean Witter Investment Management for helpful comments. In addition, we thank Patricia Kelt of GovPX for explaining their data. Financial support from the Rodney L. White Center for Financial Research at the Wharton School is gratefully acknowledged. All remaining errors are our own. The views expressed herein are those of the author and not necessarily those of the National Bureau of Economic Research.

Price Discovery in the U.S. Treasury Market:
The Impact of Orderflow and Liquidity on the Yield Curve
Michael W. Brandt and Kenneth A. Kavajecz
NBER Working Paper No. 9529
February 2003
JEL No. G0

ABSTRACT

We examine the role of price discovery in the U.S. Treasury market through the empirical relationship between orderflow, liquidity, and the yield curve. We find that orderflow imbalances (excess buying or selling pressure) can account for as much as 26 percent of the day-to-day variation in yields on days without major macroeconomic announcements. The effect of orderflow on yields is permanent and strongest when liquidity is low. All of the evidence points toward an important role of price discovery on understanding the behavior of the yield curve.

Michael W. Brandt
Finance Department
The Wharton School
University of Pennsylvania
2300 Steinberg-Dietrich Hall
Philadelphia, PA 19104-6367
and NBER
brandtm@wharton.upenn.edu

Kenneth A Kavajecz
Finance Department
The Wharton School
University of Pennsylvania
2300 Steinberg-Dietrich Hall
Philadelphia, PA 19104-6367
kavajecz@wharton.upenn.edu

The use of riskless interest rates permeates almost every facet of economics and finance. A critical issue within these disciplines is therefore to understand the behavior of the term structure of riskless interest rates, or the yield curve, which gives the mapping between the maturity of a riskless loan and its rate. Much of the term structure literature focuses on factor models in which at each point in time the yields on all bonds with different maturities are determined by the realizations of a few common factors (e.g., Vasicek, 1977; Cox, Ingersoll and Ross, 1985). The general consensus is that more than one, but not many more than three common factors capture the day-to-day variation in the yield curve. Although these factors are typically not uniquely identified, it is common to think of the factors as the level, slope, and curvature of the yield curve (e.g., Litterman and Scheinkman, 1991).

Economists are ultimately interested in understanding *why* and *how* the yield curve changes from one day to the next, which, in the context of factor models, amounts to understanding why and how the factors change over time. From a theoretical standpoint, there are two contrasting mechanisms describing changes in the yield curve. On one hand, yield curve changes can be due to public information flow, such as periodic macroeconomic announcements. The underlying assumption is that both the factor structure and the impact of public information on the factors are common knowledge among market participants. Given everyone has the same interpretation of public information, the factors and hence the yield curve immediately adjusts to new information releases, and trading in this model is strictly due to portfolio rebalancing. Empirically, there is evidence in support of this public information view in Fleming and Remolona (1997, 1999), Balduzzi, Elton, and Green (2001), and Green (2002). Moreover, acceptance of this mechanism appears to be growing, as announcement effects have recently been incorporated into term structure models (e.g. Piazzesi, 2001).

On the other hand, yield curve changes can be due to the aggregation of heterogeneous private information via the price discovery process. The assumption underlying this mechanism is that market participants either have heterogeneous information signals or different models through which public information in processed. Market participants trade when their private bond valuations differ from the market prices and through the orders they place their information is incorporated into the factors and the yield curve. Empirically, this mechanism implies that yield curve changes are not necessarily concentrated around the release of public information.

Figure 1 provides evidence consistent with this implication. The left plot displays changes in the yield of the on-the-run five-year bond on the three days surrounding the ten most influential macroeconomic announcements.[1] Consistent with the results of Fleming and Remolona (1997), there are large changes in the yield curve on days when material information is released. The right plot shows the corresponding yield changes on all other days. It is clear that there is still substantial variation in yields even in the absence of identifiable public information releases. Ultimately, we conclude that both mechanisms are likely to play a role in determining why and how the yield curve changes from one day to the next.

The term structure literature is rather agnostic about the mechanism by which the yield curve changes. Rather than analyze the underlying economic mechanisms, the majority of the literature tends to model the factors as exogenously driven stochastic processes that could represent either public information flow or price discovery. We know from many event studies that the yield curve responds to macroeconomic announcements (e.g., Fleming and Remolona, 1997, 1999; Balduzzi, Elton, and Green, 2001; Green, 2002), but there is only tangential evidence from other markets that asset prices move in response to aggregate orderflow, most notably the recent work on exchange rates by Evans and Lyons (2002a).[2] Our goal in this paper is to explore empirically the role of price discovery in the U.S. Treasury market by investigating how the yield curve changes in the absence of material public information flow. Our hypothesis is that the impact of orderflow *imbalances* (i.e., excess buying or selling pressure) on the yield curve as well as the interaction between orderflow and liquidity provides the conduit through which price discovery takes place, and that price discovery accounts for a substantial portion of the day-to-day fluctuations of the yield curve.[3]

Our empirical results strongly support this hypothesis. We find that orderflow imbalances account for up to 26 percent of the day-to-day variation of yields on days without major macroeconomic announcements. A one standard deviation excess buying (selling) pressure is associated with yields dropping (rising) by more than 2.5 basis points, which is approximately half the standard deviation of daily yield changes. We show that these changes in

[1] The announcements pertain to civilian unemployment, consumer confidence, consumer prices, FOMC meetings, housing starts, industrial production, NAPM report, non-farm payroll, producer prices, and retail sales.
[2] See also Lyons (2001a, 2001b) and Evans and Lyons (2002b).
[3] This hypothesis can be derived from a number of theoretical models that are reviewed in Lyons (2001a).

yields are permanent, at least over a two-week period following the orderflow imbalance, and are not attributed to a liquidity/inventory premium. Furthermore, we find that the relationship between yields and orderflow becomes even stronger when we condition on the liquidity in the Treasury market being low. A one standard deviation orderflow imbalance in the presence of low liquidity produces yield changes of more than 3.3 basis points and an adjusted R^2 of up to 26 percent. This is consistent with market participants paying more attention to orderflow when the true valuations are relatively uncertain (and liquidity is therefore low). Finally, we illustrate the multi-dimensional aspect and practical relevance of our results in the context of common fixed income trading strategies.

Our results have a number of important implications for both theorists and practitioners. From a modeling perspective, our findings suggest that the price discovery mechanism is a critical aspect of the factor dynamics. It follows that existing term structure models can be improved by better understanding the information structure and the way heterogeneous information is aggregated in the Treasury market. On a more fundamental level, the results help to bridge the gap between asset pricing and microstructure by demonstrating that microstructure issues, such as liquidity, can have macro implications. Finally, practitioners can use our results to determine the way their trading strategies will impact the yield curve and thereby find strategies that minimize transaction costs.

Section I describes the data and the structure we use for measuring the yield, liquidity and orderflow variables. Section II discusses the impact of orderflow on the yield curve. Section III then examines the interaction of orderflow and liquidity. Section IV analyzes the effect of common fixed income trading strategies on the yield curve, and Section V concludes.

I. Data and Preliminaries

A. Raw Data

We use intra-day U.S. Treasury security quotes and transactions for all Treasury issues. The data are obtained from GovPX, which consolidates quotes and transaction data from five of the six major inter-dealer Treasury security brokers.[4] Fleming (1997) estimates that these five brokers account for approximately two-thirds of the inter-dealer broker market, which in turn represents roughly 45 percent of the trading volume in the secondary market for Treasury securities. Our sample period covers January 1992 through December 1999.

The GovPX dataset contains security identifier information, including the CUSIP, coupon, maturity date, as well as an indicator of whether the security is trading when-issued, on-the-run, or off-the-run. The quote data contains the best bid and ask prices, associated yields, and respective bid and ask depths, all time-stamped to the nearest second. The transaction data include the time, initiator (i.e., signed trades), price and quantity. These data allow us to calculate changes in yields, net orderflow, and liquidity measures at an intra-day frequency. Our data includes 97.0 million records (89.9M quotes and 7.1M trades) on 949 CUSIPs, accounting for 69.5 trillion dollars in traded volume.

We supplement the GovPX data with information on macroeconomic announcements from Money Market Services (MMS). We have data on announcements of the latest consumer price index (CPI), producer price index (PPI), housing starts, civilian unemployment, non-farm payroll, retail sales, industrial production, consumer confidence, the NAPM reports, as well as on all FOMC meetings. For each announcement, we have the date and time of the release, the market's expectation, and the announced statistic.

B. Aggregation and Timing

To analyze the interaction among yields, orderflow, and liquidity, we must first impose a structure on the analysis that is detailed enough to capture the diversity of the data yet parsimonious enough to be manageable. Following the lead of past research we adopt a two-dimensional partition of the data. The first dimension quite naturally is the remaining *time-to-*

---

[4] GovPX covers the following inter-dealers brokers: Liberty, Tullett & Tokyo, Garban, ICAP and Hilliard Farber. Cantor Fitzgerald is the only major inter-dealer broker that is missing from the GovPX dataset. The omission of Cantor Fitzgerald results in systematically sparse data for the 30-year bond, given the prominence of Cantor Fitzgerald within the long end of the yield curve.

maturity of a security, which we split into six categories: one day to six months, six to 12 months, 12 months to two years, two to five years, five to ten years, and ten to 30 years.[5]

The second dimension is the *seasonedness* of a security, which describes how recently a security was auctioned. Similar to past research, we separate bonds into on-the-run and off-the-run. However, given the heterogeneity that exists within the set of off-the-run bonds, we further partition the off-the-run category into just off-the-run and off-the-run. Our decision to partition seasonedness in this way stems from two facts. First, the periodic auctions of the Treasury Department creates a possible link between the current on-the-run security and the incoming (when-issued) on-the-run security that we want to account for explicitly. Second, our partition is consistent with the repurchase agreement (repo) market, which is closely connected to Treasury market; where rates are segmented into on-the-run, just off-the-run and general collateral (i.e. all other securities).[6] Technically, we make the distinction between the off-the-run bonds by counting the auctions of similar maturities that occurred since the bond's issue date. Securities within one or two auctions are just off-the-run while securities outside of two auctions are off-the-run. Thus, taking the two dimensions together, we separate the data into 18 categories (six time-to-maturity categories by three seasonedness categories). Notice that the six on-the-run categories correspond simply to the six on-the-run securities (i.e., each category only includes a single CUSIP), while the just off-the-run and off-the-run categories contain a variety of securities with different issue dates and coupons (and hence different duration, convexity, etc.).

Another critical issue is the definition and proper measurement of the variables of interest. We measure net orderflow by summing the signed trade volume (purchases have a positive and sales have a negative sign) within each category over the relevant period. Because we know the initiator of the trade explicitly, this is a clean calculation, in contrast to equity market studies where the initiator of the trade often needs to be estimated (e.g., Lee and Ready, 1991). The liquidity variables, spread and depth, are measured using quote records. The quoted spread variable is defined as the difference between the ask and bid prices divided by the bid-ask spread midpoint price using only two-sided quotes for the calculation (i.e., the percent price

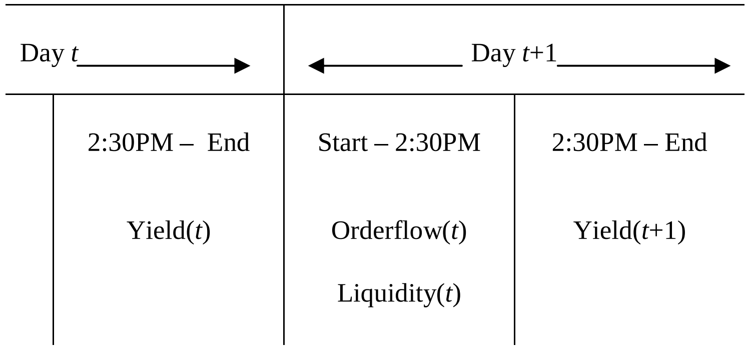
---

[5] Each category is made wide enough to include the when-issued trading of the issuing-maturity security.
[6] See Brandt, Kavajecz and Underwood (2003) for a description of the repo market and its link to the Treasury market.

spread). The quoted depth variable is the average of the bid and ask depth, where both one and two-sided quotes are used in the calculation. Both the percent quoted spread and quoted depth variables are then averaged for all bonds within each category over the relevant period.

Yield observations are obtained from transactions and bid-ask spread midpoints. The fact that the yield is a level variable (in contrast to the orderflow and liquidity variables) makes it more susceptible to contamination due to isolated transactions and stale quotes. To address this issue, we impose a filter on the yield observations at the individual security level. In particular, for each date t, we record yield observations at date t and $t+1$ (to later compute changes) for all bonds that are traded or quoted on these two consecutive days. Computing aggregate yield changes within each category with these filtered yield observations results in much less noisy series than computing yield changes with the raw yield observations, especially for off-the-run securities, because it avoids taking differences between two isolated transactions of two very different bonds (with different seasonedness, coupons, or liquidity, for example).

Finally, we employ an intra-day sampling scheme for the measurement of our variables that is driven by both institutional and technical rationales. First, the Treasury market tends to be most active in the morning, which suggests that the orderflow is likely to be concentrated in the morning. Second, because orderflow, changes in liquidity, and changes in yields do not in general occur simultaneously, there is a concern that the impact of orderflow on yields may be masked or even reversed if we measure these variables concurrently. Thus, to account for the concentration of trade in the morning as well as to minimize concerns over non-synchronous measurement, we are careful to measure our variables over separate and disjoint intervals over the course of the day. Specifically, for each category and each day in our sample, we aggregate net orderflow and average liquidity variables from the beginning of the day until 2:30 PM. In contrast, yields are averaged from 2:30 PM until the end of the trading day (See diagram below). Aggregating the variables in this way measures orderflow and liquidity during the active trading period and provides orderflow every opportunity to impact yields without the potential confounding effects of non-synchronous movements in the variables.



C. Summary Statistics and Factor Structures

Table I provides univariate summary statistics for the yields, net orderflow, bid-ask spreads, and quoted depth in our sample. Yields display the usual upward sloping nature of the yield curve. Net orderflow tends to be positive signifying net purchases; however, the standard deviations are particularly large revealing substantial variations and potential for large negative net orderflow. Lastly, the liquidity measures confirm the common notion that the more seasoned a security is, the more illiquid the market, since spreads rise and depth falls as securities move from on-the-run to just off-the-run to off-the-run.

To get a sense for the multivariate structure of the data across time-to-maturity categories in a given seasonedness category, which is how the term structure literature tends to look at the data, we begin our analysis by performing standard factor decompositions. In particular, we use principle components analysis to extract the orthogonal factors $F(t)$ from the covariance matrix of the vector $X(t)$, such that $X(t)=A+B\times F(t)$, where and A and B are matrices of constants and factor loadings, respectively. We let $X(t)$ be the (6x1) vector of yields, net orderflow, bid-ask spreads, or quoted depth within a given seasonedness category.[7]

Table II presents the results for on-the-run securities (the results for just off-the-run and off-the-run securities are very similar and are thus omitted). Consistent with the term structure literature, three factors emerge to explain 73, 26 and one percent of the variation in yields, respectively. The first factor, called the level factor, loads about equally on all maturities, with a

[7] It should be noted that our results are not sensitive to whether the factors are constructed from yields or changes in yields as has been done in the previous literature.

slight emphasis on the one- to five-year range. The second factor loads positively on long and negatively on short maturities and is called the slope factor. The third factor, called the curvature factor, loads positively on long and short maturities and negatively on medium maturities.

It is natural to conjecture that the same three factors explain the variation in the on-the-run net orderflow and liquidity variables. However, the factor decomposition for net orderflow, bid-ask spreads, and quoted depth suggest otherwise. For net orderflow, there appears to be only one predominant common factor explaining approximately 32 percent of the variation. This factor loads about equally on the net orderflow of all bonds, with a slight emphasis of the two- to five-year maturities. The remaining five factors explain approximately equal amounts of the variation of net orderflow, ranging from 16 to 11 percent. The importance of all six factors as well as the fact that net orderflow is not highly correlated across maturities, with correlations ranging from 0.1 to 0.2, suggest that the net orderflow for each maturity potentially contains independent signals for the price discovery process. The factor structures of the liquidity variables appear similar to each other and to the net orderflow factors. Like the net orderflow factors, spreads and depth contain a predominant common factor explaining between 47 and 56 percent of the variation in spreads and depth while the remaining five factors explain between three and 17 percent. Despite the similarities among some of the factors, formal pairwise comparisons of the yield, net orderflow, spreads and depth factor spaces, using the test of Chen and Robinson (1989), are rejected at the one-percent level.

In summary, the heterogeneity of yields across maturities can be effectively described using three orthogonal factors. In contrast, net orderflow, bid-ask spreads, and quoted depth all have a single dominant factor and the remaining factors all play non-trivial roles in describing the cross-sectional variation within those series. Moreover, all the factor spaces of our variables are statistically distinct suggesting that the information contained in yields, net orderflow, spreads and depth are different. We use these results to guide our modeling choices below.

II. Orderflow and the Yield Curve

A. Baseline Yield Dynamics

Motivated by the linear conditional expectations implied by the general class of affine term structure models and by the extensive macroeconomic literature modeling yields using vector autoregressions (VARs), we use as baseline model for the daily dynamics of yields a first-order VAR. However, rather than regress yields Y_t on a constant and lagged yields Y_{t-1}, we regress them on a constant and the lagged common factors (level, slope, and curvature) $F_{t-1}=L\times Y_{t-1}$, where L denotes the factor loadings.[8] Intuitively, since the three factors contain virtually all of the information in the cross-section of yields, using the factors as regressors results in an equivalent but more parsimonious description of the yield dynamics (it also overcomes the multicolinearity problem of the full VAR). More formally, our model is a restricted version of the full VAR in which the slope coefficients B^r satisfy $B^r\times L=B^u$, where B^u denotes the slope coefficients of the full VAR. We therefore refer to our baseline model as a *restricted* VAR.

Table III presents the slope coefficients, residual standard deviations, and equation-by-equation adjusted R^2 of the restricted VAR for each seasonedness category. The signs and magnitudes of the coefficients are consistent with highly persistent yields and the characteristics of the factors from Table II. A test of the restriction $B^r\times L=B^u$ is not rejected at any conventional significance level, lending formal support to our modeling choice. The most striking feature of the results is that when the regressions are expressed in yield levels the adjusted R^2 are all in excess of 98 percent but when the regressions are equivalently expressed in yield changes (by subtracting Y_{t-1} on both sides) the adjusted R^2 are virtually zero. This indicates that the yields are close to following a random walk and that the lagged yields (or factors) explain virtually none of the day-to-day *changes* in yields.

[8] Because the off-the-run categories have at times a small number of observations, there are a few instances when there is insufficient data to form the yield factors for these categories. In order to have a full set of independent variables, we interpolate the missing off-the-run yields from the corresponding on-the-run yields to form the factors. Note that the interpolation is confined to the factors alone and no dependent variable data is interpolated.

We conclude that our baseline model for the yield dynamics is successful at capturing the yield levels but effectively leaves all of the day-to-day changes in yields unexplained. The residual standard deviations indicate that the magnitude of these unexplained yield changes is substantial from an economic perspective, with standard deviations ranging from 5.1 to 9.6 basis points. Finally, Figure 1 and similar plots for the other maturities suggest that these unexplained yield changes are not solely attributed to the arrival of new information via macroeconomic announcements. Taken together, these empirical facts motivate our hypothesis that some fraction of the day-to-day yield changes is attributed to price discovery.

C. Response of Yields to Orderflow Imbalances

More specifically, our hypothesis is that orderflow, and its interaction with liquidity, are the conduit through which price discovery takes place. We first investigate the link between orderflow and yields by including orderflow imbalances, indicating *excess* buying or selling pressure, as an explanatory variable in the restricted VAR model. More specifically, for each seasonedness category, we regress the yields at time t+1 on a constant, the three yield factors at time t, and the net orderflow (demeaned and standardized) for all six bonds in that seasonedness category between time t and t+1 (recall the sampling scheme illustrated in the diagram above).

The presence of price discovery predicts a negative correlation between net orderflow and yields (excess demand pushes up prices and therefore lowers yields). One might think that such negative correlation can also be consistent with the public information flow view of yield curve movements, as long as the new information that instantaneously lowers yields *simultaneously* causes market participants to rebalance their portfolios such that demand exceeds supply. Strictly speaking, this argument is internally inconsistent. If the new information shifts market prices from one set of equilibrium prices to another, then by the definition of an equilibrium price as one that clears the market, portfolio rebalancing due to the new information cannot be systematically associated with *excess* demand or supply. The market should instantaneously clear at the new set of equilibrium prices. Nonetheless, we address this critique technically by excluding from the regressions the three days surrounding the CPI, PPI, and unemployment announcements as well as the Federal Open Market Committee (FOMC) meeting dates, which are the four most influential events for bond markets according to Fleming and

Remolona (1997). Focusing on the remaining non-announcement days is more in line with our goal of understanding how bond prices move in the absence of identifiable public information.

Table IV presents the coefficients on net orderflow along with statistics describing the regression fit (the intercept and coefficients on the lagged factors are almost identical to the ones presented in Table III and are therefore omitted). The results show overwhelmingly that net orderflow for virtually all maturities and in all three seasonedness categories is significantly negatively related to yields. Excess buyside orderflow or bond purchases raise Treasury prices and in turn lower Treasury yields and vice versa for excess sellside orderflow.[9] Furthermore, the magnitude of the coefficients is economically significant. For on-the-run bonds, for example, the coefficients on net orderflow are as large as -0.0166, which indicates that a one-standard deviation orderflow imbalance is associated with a 1.66 basis point drop in yields.

To measure the contribution of orderflow imbalance to explaining the day-to-day changes in yields, we compute for each regression an *incremental* adjusted R^2 that has the interpretation of the fraction of the variance of the *residuals* from the restricted VAR (i.e., the variation in yield *not* explained by the factors) that is explained by net orderflow. In all cases, these incremental R^2 are substantial, ranging from five to 25 percent. Interestingly, the relationship between yields and orderflow is strongest for on-the-run bonds, an issue we revisit below.

Consistent with the fact that the yields for different maturities are related by a common factor structure and that price discovery in the bond market is really concerned with the whole yield curve and the underlying factors, all yields react to net orderflow for all maturities (with only a few insignificant coefficients), as opposed to each bond reacting only to its own orderflow. Closer inspection reveals an intriguing pattern in the result. Each maturity range has a strong reaction to it own orderflow imbalance, relative to adjacent maturity ranges, but an even stronger reaction to the orderflow imbalance at the two- to five-year maturity range. The prominence of this maturity range may be institutional because the majority of fixed income portfolios, such as CMOs, are likely to have a duration near five years (the middle of the yield curve), which corresponds to the most recently issued five-year Treasury notes. Furthermore, futures trading is concentrated in the five-year note, which is consistent with the five-year future being used as a hedge instrument. The relative importance of the two- to five-year maturity

[9] Our results are consistent with Fleming (2001) who also investigates the impact of net orderflow on bond prices.

range may therefore be a product of it containing a bellwether security that is universally held and easily hedged.

Another interesting result is that the incremental R^2 are highest for the two- to five-year range and decrease monotonically for shorter and longer maturities. This pattern is exactly *opposite* to the pattern in the R^2 for the restricted VAR explaining yield changes in Table III. Even after accounting for the fact that there is more residual variance to be explained, orderflow imbalances are most important for explaining the yield changes for bonds that are relatively difficult to forecast with the yields-only baseline model.

It is worth reiterating that the results in Table IV are for non-announcement days only and are therefore unlikely to be driven by portfolio rebalancing due to transparent public information flow, which we interpret as evidence of price discovery in the private information or heterogeneous interpretation (of public information) view of how the yield curve changes. To provide further evidence in support of this view, we estimate the model with net orderflow using data for all days rather than just non-announcement days. Consistent with the hypothesis that transparent public information causes yields to shift instantaneously to a new equilibrium level and that the resulting orderflow due to portfolio rebalancing is balanced and uninformative, the relationship between yield changes and net orderflow is *weaker* in the all-days sample than in the non-announcement days sample. Specifically, the incremental R^2 for all days (also shown in Table IV) are as much as 4.5 percent smaller than for the non-announcement days.

Finally, recall from the factor analyses in Table II that net orderflow contains a common factor that accounts for about 32 percent of its variation across maturities and that the remaining variation is maturity-specific. It is therefore sensible to ask whether the relationship between orderflow imbalances and yields is due to the common component of net orderflow, the maturity specific components of net orderflow, or both. To examine this question, we replace in the regressions above (for non-announcement days) the net orderflows for all six maturities with the common factor in net orderflow. The results are shown in the last three columns of Table IV. Comparing the incremental R^2 across specifications, it is clear that most (upward of 80 percent) of the effect of orderflow imbalances on yields is due to the common factor in orderflow. Furthermore, the coefficients on the net orderflow factor are substantially larger than the coefficients on the individual net orderflows. For example, a one-standard deviation shock to the common factor (which is roughly speaking an average across maturities with a slight emphasis on the two- to five-year range – see the factor loadings in Table II) is associated with one to ten year yields changing by 2.5 basis points or more. The interpretation is that excess buying or selling across the whole curve is much more informative about the level of yields than excess buying or selling of a particular maturity range. This is perhaps not too surprising given that parallel shifts dominate the day-to-day changes in the yield curve, an issue we return to shortly.

In summary, the results in Table IV show that the negative relationship between net orderflow and yields predicted by our hypothesis of price discovery is both statistically and economically significant. Orderflow imbalances explain as much as 25 percent of the day-to-day variation in yields and a one-standard deviation imbalance across all maturities, as captured by the common factor in net orderflow, can move yields by as much as 2.8 basis points. We now explore in more depth the relationship between orderflow and yields.

As mentioned in the introduction, understanding how the yield curve changes, in the context of a factor model, amounts to understanding how the underlying factors change. We therefore examine next the relationship between orderflow imbalances and the three yield factors. Table V reports the results of regressing each on-the-run yield factor on a constant, the lagged yield factors, and on-the-run net orderflows (as in Table IV we only show a subset of the coefficients). Orderflow imbalances are strongly negatively related to changes in the level factor, with coefficients that are large in magnitude and highly significant and with an incremental R^2 of 28 percent. A one standard deviation orderflow imbalance across all maturities, as captured by the common factor in net orderflow, leads to a 5.5 basis point drop in the level factor, more than half of the standard deviation of its day-to-day changes.

The relationship between net orderflow and the slope and curvature factors is weaker. Although the coefficients have the expected signs (excess buying of short-term bonds steepens the yield curve, excess buying of long-term bonds flattens the curve, and excess buying of medium-term bonds reduces the concavity of the curve), many of the coefficients are statistically insignificant. Furthermore, the incremental R^2 of eight and five percent are not only low but must also be interpreted with some care because there is a fairly strong mechanical correlation between changes in the level and changes in the slope and curvature factors due to the loadings of the slope and curvature factors not summing to zero.[10] For example, if net orderflow explains 28 percent of the changes in the level factor and if there exists a mechanical correlation of 0.2 between changes in the level and slope factors, close to the empirical correlation, net orderflow mechanically explains about six percent of the variation in the slope factor.

We conclude from the results in Table V that the information contained in orderflow imbalances relates primarily to the level of the yield curve, explaining nearly one-third of the variation in the level factor. According to Jones (1991), approximately 87 percent of the returns on Treasury portfolios are attributed to parallel shifts in the yield curve. Together, these two facts suggest that about one-quarter of the returns are associated with price discovery.[11]

D. Price Discovery or Liquidity Premium?

Price discovery is not the only hypothesis consistent with a negative correlation between orderflow imbalances and yield changes. An ex-ante equally sensible alternative is that yields react to orderflow imbalances to compensate market participants for providing liquidity to uninformed traders, as formalized by Garman (1976) and Campbell, Grossman, and Wang (1993). For risk averse liquidity providers to be willing to absorb excess selling pressure, for example, the expected return on the offsetting long position must increase. Holding fixed the future payoffs of the securities, the only way for the expected return to increase is through a temporary drop in price and hence a rise in yield, thereby inducing the negative correlation we observe in the data. In this section, we provide three pieces of evidence that help differentiate our hypothesis of price discovery from the alternative of a liquidity/inventory premium.

The first piece of evidence is the observation in Table IV that each yield responds to orderflow imbalances across the entire yield curve as opposed to just an imbalance in its own maturity category. While this result is consistent with our notion that the market aggregates information about the underlying yield factors, it is more difficult to explain in the context of liquidity/inventory premiums. For example, why should market participants receive a greater expected return on the 12-month Treasury bill in exchange for providing liquidity in the five-

[10] Suppose the yield curve is flat at eight percent and all yields change by 25 basis points. Given the factor loadings in Table II, the slope factor increases from 1.92 to 1.98 and the curvature factor increases from 2.33 to 2.41 although the slope and curvature of the yield curve have not changed.
[11] This calculation also links the incremental R^2 in Table V to the ones in Table IV.

year bond? One possibility is that they provide liquidity across all maturities, but even then it is difficult to understand why this increase in the expected return is almost twice as large as the corresponding increase for providing liquidity in the 12-month bill itself.

More direct evidence comes from comparing the results for on-the-run bonds to those for just off- and off-the-run bonds. Besides differences in liquidity and coupon rates, bonds with different seasonedness but the same maturity are substitutes. Empirical studies on dually traded stocks as well as on spot and futures markets (e.g., Garbade and Silber, 1979, 1983) suggest that price discovery where substitutes are present tends to take place in the market that is most liquid. Liquidity premiums, on the contrary, are by definition more prevalent in illiquid markets. Comparing the results in Table IV across seasonedness categories, which are substitutes with decreasing liquidity, the incremental R^2 are substantially greater for on-the-run bonds than for the just off- and off-the-run bonds, consistent with price discovery in the liquid on-the-run bonds.

Taking this argument one step further, we include in the regressions for just off- and off-the-run yields the net orderflow for the on-the-run bonds in addition to the just off- and off-the-run net orderflow (i.e., the seasonedness category's *own* net orderflow), respectively. Under the hypothesis that price discovery takes place in the liquid on-the-run bonds, the on-the-run net orderflow should be more informative. In contrast, under the liquidity premium hypothesis, the change in yields should be more related to orderflow imbalances in the own seasonedness category. The results presented in Table VI favor overwhelmingly the price discovery hypothesis. Just off- and off-the-run yields respond much more strongly to the on-the-run net orderflow than to the own net orderflow. In fact, the own net orderflows are almost all insignificantly different from zero, suggesting that they contain no additional information.[12]

For the third piece of evidence, we exploit the different intertemporal predictions of the two hypotheses. While the impact of price discovery on yields is permanent, the liquidity premium hypothesis requires that yield changes revert quickly for liquidity providers to realize the abnormal returns over their holding period. Given the high turnover in the Treasury market, especially for on-the-run bonds, we expect this reversal to occur over the next day, which predicts a positive correlation of yield changes from dates t to $t+1$ with orderflow imbalances

[12] The off-the-run ten- to 30-year category is the only exception for which the own orderflow remains significant. However, the data for this category is very sparse due to the exclusion of Cantor Fitzgerald from GovPX.

between dates t-1 and t that roughly offsets the observed negative correlation with orderflow imbalances between dates t and t+1.[13]

In Table VII we formally test this prediction of the liquidity premium hypothesis by including in the regressions one-day lagged net orderflows in addition to contemporaneous net orderflows as explanatory variables. There is virtually no evidence that the yield changes associated with orderflow imbalances revert the subsequent day. The vast majority of the coefficients on the lagged net orderflows are *negative*, and the few positive coefficients are relatively small in magnitude. Less than ten percent of the coefficients are statistically different from zero at the ten percent level (which is consistent with the null of zero coefficients at that significance level). The adjusted incremental R^2 increase only marginally (in some cases even decrease) relative to the results in Table IV. Finally, to address the possibility of more gradual reversals, we also included further lagged net orderflows. The results, which are omitted in the tables but are available on request, show no sign of a systematic positive correlation between lagged orderflow imbalances and yield changes at *any* lag ranging from one day to two weeks. Thus, the yield changes associated with orderflow imbalances appear to be permanent.

Considering the three pieces of evidence together, we are confident that the yield changes associated with orderflow imbalances are *not* attributed to liquidity/inventory risk premiums. The evidence is instead fully consistent with (and further supportive of) our hypothesis of price discovery. However, this conclusion in no way suggests that liquidity drops out of the picture because, as we show next, liquidity plays its own role in the price discovery process.

III. Interaction of Orderflow and Liquidity

While orderflow imbalances are a critical component of the price discovery mechanism, we argue so too is the state of liquidity in the market. Specifically, orderflow imbalances in the presence of an illiquid market are likely to have a more pronounced and potentially different impact on yields than orderflow imbalances in a liquid market. A useful analogy for our view of the interplay between orderflow, liquidity, and yields is the relation between a beam of light, a

[13] Our one day reversal assumption stems from the high turnover rates in the Treasury market. As an example, the daily average transaction volume in early 2003 was $417 billion. This transaction volume is approximately 12% of the outstanding marketable debt held by the public and five times the on-the-run issues. For more on these statistics see www.ustreas.gov and www.publicdebt.treas.gov.

prism, and the color spectrum. Just as the prism alters the way the beam of light is seen, so too does the state of liquidity alter the impact of orderflow imbalances on the yield curve.

We model this interaction between orderflow and liquidity in the price discovery process by allowing in the regressions in Table IV different coefficients on net orderflow depending on whether liquidity is high or low. We proxy high or low liquidity by the bid-ask spread being below or above its median or by the quoted depth being above or below its median, respectively. Furthermore, we consider two alternative ways of conditioning on liquidity. We let the net orderflow coefficients depend either on the liquidity of the bonds for which the orderflow imbalance occurs or on the overall liquidity as proxied for by the common factor in the bid-ask spreads or quoted depths.

Figure 2 presents graphically the results of conditioning on the bid-ask spread of the bonds for which the orderflow imbalance occurs for the on-the-run category. (The results are not tabulated because there are 36 regressions per seasonedness category.) Each plot shows three sets of bars representing the yield changes across maturities resulting from a one standard deviation net orderflow imbalance in one of the six maturity categories. The black bars represent the unconditional reaction of the yield curve, corresponding to the results in Table IV. The gray and white bars represent the reaction when the liquidity of the bonds in which the orderflow imbalance occurs is high or low, respectively.

The plots reveal a number of interesting features of the data. First, consistent with the results in Table IV, positive orderflow imbalances in any of the six maturities are unconditionally associated with substantial drops in yields across the whole yield curve (black bars). Second, the reaction of the yield curve to orderflow imbalances is much stronger during periods of low liquidity than unconditionally and during periods of high liquidity, supporting our view of the interaction between orderflow and liquidity in the price discovery process. When liquidity is low (white bars), yields change by as much as 2.25 basis points in response to one standard deviation net orderflow, as opposed to 1.75 basis points unconditionally and 1.25 basis points when liquidity is high (gray bar). In relative terms, the yield changes during low liquidity are between 11 and 130 percent greater than unconditionally and between 39 and 241 percent greater than during high liquidity. Third, despite the differences in magnitude, the general shape of the reaction along the yield curve is similar across the results for different liquidity states. In particular, for each orderflow imbalance the largest reaction is for the maturity in which the imbalance occurs and the reaction diminishes the further the maturity is away from the origin of the buying pressure, thereby taking on a v-shape. Interestingly, the reaction appears to be skewed in the sense that the reaction for maturities shorter than the origin of the imbalance is muted relative to the reaction for longer maturities. Lastly, orderflow imbalances for different maturities are associated with different changes in the shape of the yield curve. Positive net orderflow at the short end of the yield curve (Treasury bills of one year or less to maturity) tends to steepen the curve. Excess buying in the middle of the yield curve (two- and five-year notes) tends to invert the curve and leads to the most pronounced reaction in magnitude. Positive net orderflow at the long end of the curve (ten-year note and 30-year bond) tends to flatten the curve and has the smallest effect in magnitude, especially for the ten-year note.

To get a sense for the statistical significance of the interaction between orderflow and liquidity, we present in Table VIII the results from conditioning on the overall liquidity as proxied for by the common factor in bid-ask spreads (panel A) or quoted depths (panel B).[14] The table shows the coefficients on net orderflow for high liquidity and the *incremental* coefficient for low liquidity (i.e., the low-liquidity coefficient is the *sum* of the two coefficients and the *t*-statistic on the incremental coefficient measures the statistical significance of the *difference* between the high- and low-liquidity coefficients). It also shows the adjusted incremental R^2 of the regression and the change in the adjusted incremental R^2 relative to the unconditional results in Table IV. Finally, to reduce the number of regressors and ease the interpretation of the result, we focus on the regressions with the first net orderflow factor instead of the entire set of net orderflows, corresponding to the last three columns in Table IV. The other results are qualitatively the same and are available on request.

The incremental coefficients for low liquidity are all negative, confirming that the drop in yields in response to excess buying is greater when liquidity is low, and most of the incremental coefficients are statistically significant at the five percent level (in 16 of 24 cases), suggesting that the difference between the high- and low-liquidity coefficients is indeed non-

---

[14] Panel B only shows results for on-the-run bonds because the quoted depth for just off and off-the-run bonds is at the median most of the time, resulting in insufficient variation in the conditioning variable.

zero. In relative terms, the low-liquidity coefficients are between 29 and 98 percent larger in magnitude than the high-liquidity coefficients. This difference is somewhat less pronounced than when the coefficients depend on the bond-specific liquidity (in Figure 2), which is consistent with our view of the interaction between orderflow and liquidity and suggests that the statistical inferences are conservative. The adjusted incremental R^2 of the regressions increase substantially, relative to the unconditional results in Table IV, especially for the on-the-run bonds in panel A (two to five percent). Finally, the results in panel B are qualitatively the same as the corresponding results in panel A, but they are quantitatively weaker because there is less variation in quoted depth than in bid-ask spreads.

In summary, the results in Figure 2 and Table VIII demonstrate that liquidity plays an important role in the price discovery process. When there is uncertainty about the true valuations, market participants provide less liquidity and update substantially their private valuations given the information revealed by the orderflow, hence yields respond about twice as strongly to an orderflow imbalance. When there is little uncertainty about the true valuations, in contrast, liquidity is high and market participants pay relatively little attention to orderflow.

IV. Common Trading Strategies

The marginal effect of an orderflow imbalance for one maturity on yields across all maturities, as illustrated in Figure 2, for example, abstracts from the fact that orderflow tends to be spread across maturities through the use of fixed income trading strategies designed to place focused bets on changes in the level and shape of the yield curve. An intuitive and practically more relevant way to get a sense for the multi-dimensional relationship between yields, orderflow, and liquidity is therefore to examine the way yields change in response to these trading strategies.

We consult the fixed income literature for the choice of common trading strategies to consider. Jones (1991) and Fabozzi (2000) describe directional interest rate trades (ladders, bullets, and barbells) as well as relative rate trades (term spreads), and Grieves (1999) examines different ways of constructing convexity trades (butterfly spreads). Guided by these discussions, we consider the following five trading strategies: (i) a ladder – an equal investment in each issuing maturity along the yield curve; (ii) a bullet – an investment at one maturity on the yield curve (note that the marginal results in Figure 2 can be interpreted in the context of bullets); (iii) a barbell – an investment in two non-adjacent maturities with the same duration as an intermediate maturity; (iv) a duration-neutral term spread – an opposite investment in the long and short-end of the yield curve with canceling duration; and (v) a duration-neutral and duration-balanced butterfly spread – an opposite investment in extreme (long and short) maturities and in an intermediate maturity with canceling duration and such that it can be split into two duration-neutral term spreads. Given the relative prominence of the five-year bond, we center all trades at the five-year maturity. We consider a five-year bullet, a barbell with the duration of a five-year bullet involving the two- and ten-year maturities, a term spread with the two- and ten-year maturities, and a butterfly spread with the two-, five-, and ten-year maturities. Finally, we set the absolute (long and short) orderflow to be \$100M, which represents a fraction of the *hourly* volume in on-the-run securities and is not uncommon for large market participants.[15]

For each of these five common fixed income trading strategies, we examine the change in yields implied by the regression results, both unconditionally and under high- or low-liquidity conditions as captured by the common factor in bid-ask spreads. Figure 3 presents the results in the same format as Figure 2 (i.e., the black, white, and gray bars are the unconditional, low-, and high-liquidity responses, respectively). Consider first the ladder, five-year bullet, and five-year barbell strategies, which all involve positive orderflows and are therefore associated with a drop in yields across all maturities. Of these three strategies, the bullet has the strongest effect on yields (as much as 1/3 basis point), especially for medium maturities and when liquidity is low. However, not only is the magnitude of the response for the ladder and barbell smaller, but the way the shape of the yield curve changes is also very different. The bullet has a v-shaped response, centered at the five-year maturity, and therefore leads to a downward shift and straightening (i.e., decrease in concavity) of the yield curve. The ladder and barbell, in contrast, have relatively small effects on very short maturities (one year and less) and roughly equal effects on all other maturities, resulting in a parallel shift of the yield curve with a flattening (i.e., decrease in slope) at the very short end. Finally, the response to the bullet is somewhat more sensitive to liquidity than the responses to the ladder and barbell.

---

[15] More specifically, the five trading strategies involve the following positions: (i) ladder – long \$16.67M in each of the six-month and one-year bills, two-, five-, and ten-year notes, and 30-year bond; (ii) bullet – long \$100M in the five-year note; (iii) barbell – long \$54.9M in the two-year note and \$45.1M in the ten-year note; (iv) term spread – short \$80.4M in the two-year note and long \$19.6M in the ten-year note; and (v) butterfly spread – long \$48.1M and \$11.7M in the two- and ten-year notes, respectively, and short \$40.2M in the five-year note.

The differences between the results for the bullet and barbell strategies are particularly intriguing because the barbell has by design the same duration and hence the same first-order exposure to short-term interest rate movements as the bullet. The fact that the response to the bullet is between 33 and 119 percent greater (46 and 135 percent when liquidity is low) and that the shape of the responses is quite different suggests that excess buying or selling of the five-year bond carries information beyond a directional bet on short-term interest rates. From a practical perspective, it also implies that the barbell is a considerably cheaper way of buying five-year duration because it involves a smaller price impact and therefore lower transaction costs.

The term spread, which involves buying the ten-year bond and selling the two-year note such that the durations of the two positions cancel, leads to an upward shift and bowing (i.e., increase in concavity) of the yield curve. Mechanically, the upward shift is consistent with the fact that the term spread involves more negative than positive orderflow because the duration of the ten-year bond is roughly four times that of the two-year note. At a more conceptual level, however, the fact that a duration-neutral trading strategy is associated with a shift in the yield curve is somewhat surprising and suggests again that the information contained in orderflow is more complex than a directional bet on short-term interest rates. The bowing of the yield curve is more intuitive. Since the term spread represents a bet that the two-year yield will rise (its price will drop) relative to the ten-year yield, the yield increase in response to the orderflow is 71 percent greater at the two-year maturity than at the ten-year maturity. The results for the butterfly spread are equally intuitive. The butterfly spread involves selling the five-year note and buying the two-year note and ten-year bond such that the durations cancel and the position can be split into two duration-neutral term spreads. It represents a bet that the yield on the middle maturity will rise relative to the yields on the extreme maturities, resulting in a more concave yield curve. Consistent with this bet, the orderflow leads to an increase in the medium maturity yields and leaves the short- and long-maturity yields unchanged.

Comparing rows in Figure 3, the role of liquidity is very different for the directional strategies in the first row than for the spread strategies in the second row. For the directional strategies, the yield response is much more pronounced when liquidity is low than when it is high, consistent with the results in the previous section and our view that market participants pay more attention to orderflow when the true valuation is uncertain and liquidity is low. For the spread strategies, in contrast, the yield response is far less sensitive to liquidity. The relative difference between the low- and high-liquidity responses for the term spread, for instance, ranges from six to 64 percent, compared to 78 to 150 percent for the bullet strategy. The reason for this difference is that for the spread strategies each leg of the position has a more pronounced effect on yields when liquidity is low but in aggregate the low-liquidity increments partially cancel.

In summary, the results for the common fixed income trading strategies show how different combinations of orderflow can lead to substantially different changes in the level and shape of the yield curve. Even two strategies with the same duration elicit distinct yield responses. Furthermore, a sequence of realistic trades can account in magnitude for the typical day-to-day changes in the yield curve. For example, a sequence of ladder trades totaling $2B, which accounts for a small fraction of the daily volume in on-the-run Treasuries, shifts the yield curve by four basis points unconditionally and by six basis points when liquidity is low, which is approximately the daily standard deviation of yield changes. Finally, the role of liquidity depends on the context of the orderflow and is very different for directional strategies with strictly positive or negative orderflow than for spread strategies with mixed orderflow.

V. Conclusion

We examined the role of price discovery in the U.S. Treasury market through the empirical relationship between orderflow, liquidity, and the yield curve. Our hypothesis is that, in the absence of material public information flow, orderflow imbalances account for a substantial portion of the day-to-day fluctuations of the yield curve and that the role of orderflow depends on the liquidity in the Treasury market.

Our empirical results strongly support this hypothesis. Unconditionally, orderflow imbalances account for up to 21 percent of the day-to-day variation of yields on days without major macroeconomic announcements. A one standard deviation excess buying (selling) pressure is associated with yields dropping (rising) by more than 2.5 basis points, which is approximately half the standard deviation of daily yield changes. The changes in yields appear permanent and are not attributed to a liquidity/inventory premium. The evidence is even stronger when we condition on the liquidity in the Treasury market being low. Net orderflow then accounts for up to 26 percent of the day-to-day variation of yields, and a one-standard deviation imbalance is associated with yields changing by more than 3.3 basis points. We argued that this finding is consistent with market participants paying more attention to orderflow when the true valuations are uncertain. Finally, we illustrated the multi-dimensional aspect and practical relevance of our results in the context of common fixed income trading strategies.

References

Balduzzi, Pierluigi, Edwin J. Elton, and T. Clifton Green, 2001, Economic news and bond prices: Evidence from the U.S. Treasury market, *Journal of Financial and Quantitative Analysis* 36, 523-543.

Brandt, Michael W., Kenneth A. Kavajecz and Shane Underwood, 2003, An analysis of the repurchase agreement market, Working Paper, University of Pennsylvania.

Campbell, John Y., Sanford J. Grossman and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics* 108, 905-939.

Chen, K.H., and John Robinson, 1989, Comparison of factor spaces of two related populations, *Journal of Multivariate Analysis* 28, 190-203.

Cox, John C., Jonathan E. Ingersoll, Jr., and Stephen A. Ross, 1985, A theory of the term structure of interest rates, *Econometrica* 53, 385-408.

Evans, Martin D.D., and Richard K. Lyons, 2002a, Orderflow and exchange rate dynamics, *Journal of Political Economy* 110, 170-180.

Evans, Martin D.D., and Richard K. Lyons, 2002b, How is macro news transmitted to exchange rates?, Working Paper, Georgetown University.

Fabozzi, Frank J., 2000, *Bond Markets, Analysis and Strategies*, Prentice Hall: Upper Saddle River, NJ.

Fleming, Michael J., 1997, The round-the-clock market of U.S. Treasury securities, Federal Reserve Bank of New York *Economic Policy Review*, 9-32.

Fleming, Michael J., 2001, Measuring Treasury Market Liquidity, Working Paper, Federal Reserve Bank of New York.

Fleming, Michael J., and Eli M. Remolona, 1997, What moves the bond market?, Federal Reserve Bank of New York *Economic Policy Review*, 31-51.

Fleming, Michael J., and Eli M. Remolona, 1999, Price formation and liquidity in the U.S. treasuries market: The response to public information, *Journal of Finance* 54, 1901-1915.

Garbade, Kenneth D., and William L. Silber, 1979, Dominant and satellite markets: A study of dually traded securities, *Review of Economics and Statistics* 61, 455-460.

Garbade, Kenneth D., and William L. Silber, 1983, Price movements and price discovery in futures and cash markets, *Review of Economics and Statistics* 65, 289-297.

Garman, Mark B., 1976, Market microstructure, *Journal of Financial Economics* 3, 257-275.

Green Clifton T., 2002, Economic News and the Impact of Trading on Bond Prices. Working paper, Emory University.

Grieves, Robin, 1999, Butterfly trades, *Journal of Portfolio Management* 26, 87-95.

Jones, Frank J., 1991, Yield curve strategies, *Journal of Fixed Income* 1, 43-51.

Lee, Charles and Mark Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733-746.

Litterman, Robert, and Jose Scheinkman, 1991, Common factors affecting bond returns, *Journal of Fixed Income* 1, 54-61.

Lyons, Richard K., 2001a, *The Microstructure Approach to Exchange Rates*, MIT Press: Boston, MA.

Lyons, Richard K., 2001b, New perspective on FX markets: Order-flow analysis, *International Finance* 4, 303-320.

Vasicek, Oldrich, 1977, An equilibrium characterization of the term structure, *Journal of Financial Economics* 5, 177-188.

Piazzesi, Monika, 2001, An econometric model of the yield curve with macroeconomic jump effects, Working Paper, UCLA.

Table I: Summary Statistics

This table presents means and standard deviations [in brackets] of yields, net orderflow (purchases less sales), percentage price bid-ask spreads, and quoted depth over the period January 1992 through December 1999 for the GovPX dataset. Securities are grouped by the remaining time-to-maturity and seasonedness, where seasonedness is separated into on-the-run (when-issued trading plus the most recently auctioned security), just off-the-run (securities having either one or two new issues of similar maturity auctioned since being issued), and off-the-run (securities having three or more new issues of similar maturity auctioned since being issued).

	Remaining Time to Maturity					
Seasonedness	0-6 months	6-12 months	1-2 years	2-5 years	5-10 years	10-30 years
	Yields (%)					
On-the-Run	4.787 [0.928]	4.984 [0.948]	5.432 [0.874]	5.826 [0.797]	6.313 [0.801]	6.751 [0.806]
Just Off-the-Run	4.841 [0.912]	4.964 [0.937]	5.419 [0.889]	5.815 [0.803]	6.515 [0.739]	6.970 [0.623]
Off-the-Run	4.764 [0.926]	4.985 [0.948]	5.290 [0.912]	5.806 [0.789]	6.412 [0.800]	6.977 [0.748]
	Net Orderflow ($Mil.)					
On-the-Run	22.443 [322.111]	-52.082 [372.891]	246.909 [594.361]	307.857 [604.659]	144.651 [343.624]	22.884 [121.397]
Just Off-the-Run	12.250 [145.323]	-6.662 [110.529]	29.838 [115.934]	21.797 [89.382]	7.555 [46.129]	4.494 [39.263]
Off-the-Run	29.945 [3871.440]	67.652 [228.883]	86.873 [250.132]	52.243 [138.983]	5.371 [54.497]	0.958 [20.840]
	Bid-Ask Spreads (% of Midpoint Price)					
On-the-Run	0.033 [0.017]	0.056 [0.029]	0.075 [0.030]	0.129 [0.043]	0.235 [0.066]	0.553 [0.153]
Just Off-the-Run	0.067 [0.052]	0.138 [0.079]	0.209 [0.097]	0.350 [0.119]	0.605 [0.149]	0.646 [0.211]
Off-the-Run	0.123 [0.049]	0.210 [0.077]	0.329 [0.105]	0.508 [0.148]	0.736 [0.203]	0.740 [0.214]
	Quoted Depth ($Mil.)					
On-the-Run	15.207 [6.718]	15.276 [4.492]	18.034 [7.577]	8.188 [2.115]	6.488 [2.212]	2.171 [0.762]
Just Off-the-Run	8.773 [4.252]	6.861 [2.485]	4.779 [2.675]	2.789 [0.828]	1.426 [1.130]	1.721 [1.808]
Off-the-Run	5.434 [2.374]	3.923 [1.749]	1.892 [0.538]	1.122 [0.350]	1.223 [0.769]	1.419 [1.075]

Table II: Factor Structures

This table presents the loadings of orthogonal factors extracted from the covariance matrix of on-the-run yields, net orderflow (purchases less sales), percentage bid-ask spreads, and quoted depth for six maturity categories. The factors are ordered by the percent of the total variation explained by each factor (% Explained).

	Factors					
Maturity	1st	2nd	3rd	4th	5th	6th
	Yields					
0-6 months	0.3956	-0.4358	0.6403	0.2925	0.3899	0.0785
6-12 months	0.4231	-0.3686	0.0820	-0.2713	-0.7074	-0.3230
1-2 years	0.4644	-0.1793	-0.4273	-0.3366	0.1501	0.6586
2-5 years	0.4715	0.1178	-0.4348	0.1023	0.4164	-0.6252
5-10 years	0.3887	0.4602	-0.0272	0.6549	-0.3778	0.2543
10-30 years	0.2745	0.6453	0.4593	-0.5368	0.0943	-0.0158
% Explained	0.7274	0.2648	0.0058	0.0013	0.0006	0.0001
	Net Orderflow					
0-6 months	0.3201	-0.5345	0.7325	-0.1456	-0.2320	0.0172
6-12 months	0.4001	-0.1994	-0.1395	0.8740	0.0316	0.1257
1-2 years	0.4351	-0.3094	-0.4034	-0.4197	0.3407	0.5099
2-5 years	0.5172	-0.0019	-0.2044	-0.1575	0.1116	-0.8084
5-10 years	0.4085	0.4244	-0.1371	-0.1152	-0.7588	0.2127
10-30 years	0.3374	0.6314	0.4699	0.0240	0.4908	0.1587
% Explained	0.3237	0.1602	0.1451	0.1360	0.1294	0.1057
	Bid-Ask Spreads					
0-6 months	0.3679	-0.2156	0.6911	0.5778	0.0798	-0.0181
6-12 months	0.4067	-0.0029	0.4510	-0.7785	-0.1332	0.0859
1-2 years	0.4354	0.4406	-0.1974	0.0486	0.6346	0.4150
2-5 years	0.4916	0.1146	-0.2593	0.0087	0.0397	-0.8224
5-10 years	0.4697	0.0431	-0.3265	0.2160	-0.7043	0.3580
10-30 years	0.2178	-0.8628	-0.3258	-0.1050	0.2747	0.1247
% Explained	0.5610	0.1651	0.1166	0.0810	0.0452	0.0311
	Quoted Depth					
0-6 months	0.2681	0.1801	-0.8110	-0.4820	0.0700	-0.0265
6-12 months	0.3717	0.2151	-0.3124	0.8339	0.1494	0.0118
1-2 years	0.5267	-0.0076	0.1927	-0.0660	-0.4747	-0.6750
2-5 years	0.5281	-0.1374	0.1408	-0.0897	-0.3785	0.7288
5-10 years	0.4810	-0.1996	0.2965	-0.1898	0.7751	-0.0643
10-30 years	-0.0478	-0.9287	-0.3158	0.1543	-0.0585	-0.0909
% Explained	0.4711	0.1706	0.1537	0.1113	0.0553	0.0380

Table III: Response of Yields to Lagged Factors

This table presents the results of regressing yields of six maturity categories at date *t* on the first three yield factors (level, slope, and curvature) at date *t*-1. The regressions include intercepts that are not tabulated. The subpanels are for three different seasonedness categories – on-the-run, just off-the-run, and off-the-run bonds. The table also shows adjusted R^2 for regressions in both levels and changes. * (**) [***] represent significance levels of 10%, 5%, and 1%, respectively.

	Factors				Adjusted R^2	
Maturity	Level	Slope	Curvature	Res Std	Levels	Changes
			On-the-Run			
0-6 months	0.3806***	-0.4313***	0.6210***	0.0505	99.70%	1.09%
6-12 months	0.4400***	-0.3826***	0.0669***	0.0672	99.50%	0.61%
1-2 years	0.4719***	-0.1747***	-0.4390***	0.0577	99.57%	0.46%
2-5 years	0.4519***	0.1193***	-0.4268***	0.0595	99.44%	0.41%
5-10 years	0.3864***	0.4531***	-0.0625***	0.0675	99.28%	0.55%
10-30 years	0.2808***	0.6464***	0.4608***	0.0509	99.60%	0.64%
			Just Off-the-Run			
0-6 months	0.3911***	-0.4253***	0.5935***	0.0584	99.59%	0.53%
6-12 months	0.4243***	-0.3893***	0.1336***	0.0642	99.53%	0.51%
1-2 years	0.4534***	-0.2109***	-0.3827***	0.0825	99.14%	0.34%
2-5 years	0.4366***	0.0779***	-0.6339***	0.0738	99.15%	0.18%
5-10 years	0.4003***	0.4682***	0.0689***	0.0838	98.72%	0.29%
10-30 years	0.3208***	0.6327***	0.3563***	0.0639	98.95%	0.42%
			Off-the-Run			
0-6 months	0.4018***	-0.5504***	0.5573***	0.0538	99.66%	0.73%
6-12 months	0.4118***	-0.4187***	-0.0386***	0.0530	99.69%	0.59%
1-2 years	0.4172***	-0.1937***	-0.5463***	0.0720	99.37%	0.52%
2-5 years	0.4092***	0.2418***	-0.5171***	0.0720	99.16%	0.44%
5-10 years	0.4125***	0.4344***	0.0519***	0.0958	98.55%	0.58%
10-30 years	0.3852***	0.4847***	0.6091***	0.0801	98.86%	0.69%

Table IV: Response of Yields to Orderflow

This table presents the results of regressing yields of six maturity categories at date *t* on net orderflow (purchases less sales) between dates *t*-1 and *t*. The regressions are for non-announcement days and include intercepts and coefficients on the first three yield factors at date *t*-1 that are not tabulated. The subpanels are for three different seasonedness categories – on-the-run, just off-the-run, and off-the-run bonds. The adjusted R^2 measures the incremental contribution of net orderflow relative to regressions that include only the lagged yield factors. For comparison, the table also shows the adjusted R^2 for all days and the results of regressing yields on the first net orderflow factor. * (**) [***] represent significance levels of 10%, 5% and 1%, respectively.

	Net Orderflow by Maturity									1st Net Orderflow Factor		
Maturity	0-6 mths	6-12 mths	1-2 yrs	2-5 yrs	5-10 yrs	10-30 yrs	Res Std	Adj R^2	All Days Adj R^2	Factor	Res Std	Adj R^2
						On-the-Run						
0-6 months	-0.0072***	-0.0030**	-0.0060***	-0.0090***	-0.0010	-0.0013	0.0438	10.61%	9.57%	-0.0147***	0.0540	10.21%
6-12 months	-0.0050***	-0.0091***	-0.0070***	-0.0114***	-0.0028	-0.0031***	0.0596	15.37%	13.51%	-0.0229***	0.0599	13.80%
1-2 years	-0.0061***	-0.0062***	-0.0096***	-0.0133***	-0.0030*	-0.0042***	0.0476	21.15%	18.83%	-0.0248***	0.0478	19.79%
2-5 years	-0.0068***	-0.0057***	-0.0092***	-0.0166***	-0.0032**	-0.0049***	0.0496	24.67%	20.19%	-0.0263***	0.0498	21.37%
5-10 years	-0.0038***	-0.0043***	-0.0070***	-0.0149***	-0.0050**	-0.0054***	0.0590	19.15%	17.61%	-0.0278***	0.0593	17.81%
10-30 years	-0.0022	-0.0028**	-0.0064***	-0.0097***	-0.0047***	-0.0064***	0.0461	15.58%	12.31%	-0.0165***	0.0463	13.42%
						Just Off-the-Run						
0-6 months	-0.0056***	-0.0047***	-0.0055***	-0.0083**	-0.0028	0.0004	0.0540	4.68%	3.51%	-0.0091***	0.0544	3.62%
6-12 months	-0.0041***	-0.0088***	-0.0069***	-0.0116***	-0.0035*	-0.0056***	0.0571	15.10%	14.93%	-0.0236***	0.0573	14.78%
1-2 years	-0.0043**	-0.0086***	-0.0095***	-0.0140***	-0.0045*	-0.0061***	0.0731	16.00%	13.65%	-0.0304***	0.0733	14.85%
2-5 years	-0.0059***	-0.0081***	-0.0104***	-0.0184***	-0.0052**	-0.0046**	0.0619	17.37%	15.94%	-0.0273***	0.0620	16.34%
5-10 years	-0.0091***	-0.0077***	-0.0098***	-0.0131***	-0.0075***	-0.0039**	0.0739	15.69%	14.30%	-0.0234***	0.0742	14.46%
10-30 years	0.0000	-0.0057**	-0.0057*	-0.0094***	-0.0053**	-0.0033*	0.0548	16.07%	15.70%	-0.0231***	0.0554	15.25%
						Off-the-Run						
0-6 months	-0.0051***	-0.0043***	-0.0029*	-0.0036**	-0.0002	-0.0016	0.0482	5.09%	4.40%	-0.0099***	0.0484	4.72%
6-12 months	-0.0044***	-0.0072***	-0.0068***	-0.0074***	-0.0027*	-0.0063	0.0430	16.45%	16.19%	-0.0193***	0.0434	15.42%
1-2 years	-0.0054***	-0.0065***	-0.0096***	-0.0137***	-0.0035**	-0.0037*	0.0612	16.33%	14.27%	-0.0283***	0.0614	15.91%
2-5 years	-0.0050***	-0.0056***	-0.0082***	-0.0168***	-0.0038**	-0.0064*	0.0614	14.53%	13.81%	-0.0252***	0.0616	13.88%
5-10 years	-0.0064**	-0.0042***	-0.0100***	-0.0120**	-0.0043***	-0.0079**	0.0856	13.41%	12.97%	-0.0240***	0.0862	11.78%
10-30 years	0.0084	-0.0035	-0.0200***	-0.0050	-0.0024**	-0.0081**	0.0713	12.60%	11.39%	-0.0270***	0.0752	9.79%

Table V: Response of Yield Factors to Orderflow

This table presents the results of regressing the first three on-the-run yield factors (level, slope, and curvature) at date *t* on net orderflow (purchases less sales) between dates *t*-1 and *t*. The regressions are for non-announcement days and include intercepts and coefficients on the yield factors at date *t*-1 that are not tabulated. The adjusted R^2 measure the incremental contribution of net orderflow relative to regressions that include only the lagged yield factors. For comparison, the table also shows the results of regressing the yield factors on the first net orderflow factor. * (**) [***] represent significance levels of 10%, 5% and 1%, respectively.

	Net Orderflow by Maturity								1st Net Orderflow Factor		
Factors	0-6 mths	6-12 mths	1-2 yrs	2-5 yrs	5-10 yrs	10-30 yrs	Res Std	Adj R^2	Factor	Res Std	Adj R^2
Level	-0.0121 ***	-0.0157 ***	-0.0184 ***	-0.0286 ***	-0.0070 **	-0.0100 ***	0.0863	28.14%	-0.0550 ***	0.0868	27.68%
Slope	0.0018	-0.0010	-0.0022 *	-0.0051 ***	-0.0033 ***	-0.0010	0.0346	8.27%	-0.0071 ***	0.0348	7.67%
Curvature	0.0003	0.0016 **	0.0014 **	0.0029 ***	-0.0006	0.0007	0.0204	4.95%	0.0042 ***	0.0204	3.77%

Table VI: Response of Off-the-Run Yields to Own versus On-the-Run Orderflow

This table presents the results of regressing off-the-run yields of six maturity categories at date *t* on off-the-run and on-the-run net orderflow (purchases less sales) between dates *t*-1 and *t*. The regressions are for non-announcement days and include intercepts and coefficients on the first three yield factors at date *t*-1 that are not tabulated. The subpanels are for two different seasonedness categories – just off-the-run and off-the-run bonds. The adjusted R^2 measure the incremental contribution of net orderflow relative to regressions that include only the lagged yield factors. ΔAdj R^2 denotes the change in the adjusted R^2 relative to the results in Table IV. * (**) [***] represent significance levels of 10%, 5% and 1%, respectively.

	Own Net Orderflow by Maturity						On-the-Run Net Orderflow by Maturity							
Maturity	0-6 mths	6-12 mths	1-2 yrs	2-5 yrs	5-10 yrs	10-30 yrs	0-6 mths	6-12 mths	1-2 yrs	2-5 yrs	5-10 yrs	10-30 yrs	Adj R^2	ΔAdj R^2
							Just Off-the-Run							
0-6 mths	-0.0013	-0.0004	-0.0006	-0.0003	-0.0002	0.0046*	-0.0021***	-0.0037***	-0.0069**	0.0043**	-0.0028	-0.0030	5.03%	0.35%
6-12 mths	-0.0080*	0.0015	-0.0016	0.0008	-0.0004	0.0015	-0.0015**	-0.0056***	-0.0047***	-0.0108***	-0.0054	-0.0034	15.28%	0.18%
1-2 yrs	-0.0042	0.0000	-0.0031	-0.0004	-0.0046*	-0.0064*	-0.0061**	-0.0052**	-0.0099***	-0.0177***	-0.0098**	-0.0045*	15.98%	-0.02%
2-5 yrs	-0.0070	-0.0001	-0.0059	0.0033	0.0011	-0.0002	-0.0042**	-0.0040**	-0.0082**	-0.0132**	-0.0125***	-0.0072**	17.32%	-0.05%
5-10 yrs	0.0025	-0.0010	-0.0059	-0.0035	-0.0033	-0.0040	-0.0093**	-0.0032	-0.0057	-0.0100***	-0.0146***	-0.0108**	15.69%	0.00%
10-30 yrs	-0.0024	0.0037*	-0.0055	0.0021	0.0002	-0.0003	-0.0002	-0.0055*	-0.0033	-0.0139**	-0.0109***	-0.0113***	16.33%	0.26%
							Off-the-Run							
0-6 mths	-0.0142	-0.0101	-0.0011	-0.0001	-0.0052	0.0065	-0.0025***	-0.0059**	-0.0016	-0.0079	-0.0032	-0.0029**	5.44%	0.35%
6-12 mths	0.0015	-0.0156	-0.0067	0.0004	-0.0076*	0.0068*	-0.0053**	-0.0031***	-0.0061**	-0.0081**	-0.0017	-0.0069*	16.64%	0.19%
1-2 yrs	0.0151*	-0.0060	-0.0064*	0.0011	-0.0053	-0.0017	-0.0017**	-0.0038***	-0.0079***	-0.0134**	-0.0083	-0.0081*	16.37%	0.04%
2-5 yrs	-0.0276*	-0.0162*	-0.0031	-0.0092*	-0.0054	0.0096*	-0.0072*	-0.0024*	-0.0013**	-0.0136***	-0.0106*	-0.0096**	14.52%	-0.01%
5-10 yrs	0.0188*	-0.0289*	-0.0040	0.0007	-0.0084*	0.0032	-0.0014	-0.0090	-0.0076	-0.0114**	-0.0146**	-0.0104***	13.48%	0.07%
10-30 yrs	-0.0068	0.0030	-0.0005	-0.0026	-0.0031	-0.0127*	-0.0117	-0.0040	-0.0065	-0.0107**	-0.0183**	-0.0125**	12.71%	0.11%

Table VII: Response of Yields to Contemporaneous and Lagged Net Orderflow

This table presents the results of regressing yields of six maturity categories at date *t* on contemporaneous net orderflow (purchases less sales) between dates *t*-1 and *t* and on lagged net orderflow between dates *t*-2 and *t*-1. The regressions are for non-announcement days and include intercepts and coefficients on the first three yield factors at date *t*-1 that are not tabulated. The subpanels are for three different seasonedness categories – on-the-run, just off-the-run, and off-the-run bonds. The adjusted R^2 measure the incremental contribution of net orderflow relative to regressions that include only the lagged yield factors. ΔAdj R^2 denotes the change in the adjusted R^2 relative to the results in Table IV. * (**) [***] represent significance levels of 10%, 5% and 1%, respectively.

	Contemporaneous Net Orderflow by Maturity						Lagged Net Orderflow by Maturity							
Maturities	0-6 mths	6-12 mths	1-2 yrs	2-5 yrs	5-10 yrs	10-30 yrs	0-6 mths	6-12 mths	1-2 yrs	2-5 yrs	5-10 yrs	10-30 yrs	Adj R^2	ΔAdj R^2
							On-the-Run							
0-6 mths	-0.0065***	-0.0041**	-0.0054***	-0.0061***	-0.0007	-0.0013	0.0008	-0.0011	-0.0003	-0.0009	0.0009	-0.0019	10.06%	-0.55%
6-12 mths	-0.0055***	-0.0102***	-0.0066***	-0.0097***	-0.0022	-0.0065***	0.0022	-0.0038*	-0.0030	-0.0015	-0.0008	-0.0029	15.68%	0.31%
1-2 yrs	-0.0062***	-0.0072***	-0.0095***	-0.0110***	-0.0022**	-0.0047***	0.0027	-0.0009	-0.0029*	-0.0007	-0.0012	-0.0052 *	21.38%	0.23%
2-5 yrs	-0.0068***	-0.0079***	-0.0102***	-0.0122***	-0.0029**	-0.0038**	0.0015	-0.0017	-0.0021	-0.0019	0.0003	-0.0045 *	25.18%	0.51%
5-10 yrs	-0.0044**	-0.0097***	-0.0067***	-0.0154***	-0.0022***	-0.0043**	0.0011	-0.0057*	-0.0016	-0.0055*	-0.0017	-0.0020	19.85%	0.70%
10-30 yrs	-0.0019	-0.0045**	-0.0064***	-0.0066***	-0.0043***	-0.0038**	0.0030*	-0.0004	-0.0028	-0.0003	-0.0005	-0.0025 *	15.96%	0.38%
							Just Off-the-Run							
0-6 mths	-0.0051***	-0.0058***	-0.0059***	-0.0018*	0.0025	0.0008	-0.0022	-0.0007	0.0018	0.0054	0.0017	0.0010*	5.36%	0.68%
6-12 mths	-0.0044***	-0.0102***	-0.0068***	-0.0102***	-0.0029***	-0.0063***	0.0019	-0.0035	-0.0025	-0.0013	-0.0021	-0.0030*	15.78%	0.68%
1-2 yrs	-0.0059***	-0.0080***	-0.0087***	-0.0175***	-0.0048***	-0.0066**	0.0076	-0.0036	-0.0024*	-0.0073	0.0007	-0.0046	17.16%	1.16%
2-5 yrs	-0.0057***	-0.0086***	-0.0119***	-0.0116***	-0.0028**	-0.0037**	-0.0007	-0.0002*	-0.0041	0.0034	-0.0028	-0.0022	17.14%	-0.23%
5-10 yrs	-0.0098***	-0.0090***	-0.0077***	-0.0095***	-0.0045**	-0.0032**	0.0028	-0.0094	-0.0014	-0.0022	0.0068	-0.0023	15.46%	-0.23%
10-30 yrs	0.0011	-0.0051**	-0.0063*	-0.0071**	-0.0098*	-0.0039**	0.0000	0.0029	-0.0047	-0.0046	-0.0023	-0.0032	14.12%	-1.95%
							Off-the-Run							
0-6 mths	-0.0051***	-0.0034**	-0.0034*	-0.0032*	-0.0009	-0.0010	0.0002	-0.0031	-0.0017	0.0036	0.0003	-0.0017	4.78%	-0.31%
6-12 mths	-0.0044***	-0.0079***	-0.0070***	-0.0068***	-0.0030**	-0.0059	-0.0003	-0.0016	-0.0008	0.0005	-0.0010	-0.0027	16.94%	0.49%
1-2 yrs	-0.0047***	-0.0081***	-0.0089***	-0.0151***	-0.0026**	-0.0034	0.0017	-0.0016	-0.0032	-0.0046	-0.0024	-0.0023	16.07%	-0.26%
2-5 yrs	-0.0054***	-0.0066***	-0.0100***	-0.0129***	-0.0034***	-0.0053**	0.0030	-0.0009	-0.0005	-0.0010	0.0000	-0.0058	15.28%	0.75%
5-10 yrs	-0.0072**	-0.0055***	-0.0101***	-0.0051**	-0.0045***	-0.0060**	0.0021	-0.0115	-0.0019	0.0042	0.0021	-0.0009	12.55%	-0.86%
10-30 yrs	0.0100	-0.0035**	-0.0251***	-0.0028	-0.0021***	-0.0088**	0.0040	0.0046	0.0032	-0.0032	-0.0136	-0.0047	11.57%	-1.03%

Table VIII: Response of Yields to Orderflow Conditional on Liquidity

This table presents the results of regressing yields of six maturity categories at date *t* on the first net orderflow factor and on the product of the first net orderflow factor with a dummy variable for low liquidity between dates *t*-1 and *t*. The dummy variable equals one when liquidity is low and zero otherwise, where low liquidity is proxied by the first factor in bid-ask spreads being above its median (in panel A) or the first factor in quoted depth being below its median (in panel B). The regressions are for non-announcement days and include intercepts and coefficients on the first three yield factors at date *t*-1 that are not tabulated. The subpanels are for three different seasonedness categories – on-the-run, just off-the-run, and off-the-run bonds. The adjusted R^2 measure the incremental contribution of net orderflow relative to regressions that include only the lagged yield factors. ΔAdj R^2 denotes the change in the adjusted R^2 relative to the results in Table IV. * (**) [***] represent significance levels of 10%, 5% and 1%, respectively.

	1st Net Orderflow Factor			
Maturities	High Liquidity	Low Liquidity Increment	Adj R^2	ΔAdj R^2
		Panel A: Liquidity Proxied by Bid-Ask Spreads		
		On-the-Run		
0-6 months	-0.0102 ***	-0.0077 **	12.47%	2.26%
6-12 months	-0.0177 ***	-0.0093 ***	16.93%	3.13%
1-2 years	-0.0189 ***	-0.0107 ***	24.84%	5.05%
2-5 years	-0.0208 ***	-0.0117 ***	26.34%	4.97%
5-10 years	-0.0209 ***	-0.0130 ***	21.40%	3.59%
10-30 years	-0.0150 ***	-0.0042 *	16.15%	2.73%
		Just Off-the-Run		
0-6 months	-0.0074 ***	-0.0041 *	4.65%	1.03%
6-12 months	-0.0186 ***	-0.0118 ***	16.96%	2.18%
1-2 years	-0.0251 ***	-0.0122 ***	17.34%	2.49%
2-5 years	-0.0217 ***	-0.0131 ***	19.15%	2.81%
5-10 years	-0.0204 ***	-0.0096 **	16.51%	2.05%
10-30 years	-0.0206 ***	-0.0070 *	16.37%	1.12%
		Off-the-Run		
0-6 months	-0.0062 ***	-0.0061 *	4.79%	0.07%
6-12 months	-0.0149 ***	-0.0087 **	16.96%	1.54%
1-2 years	-0.0226 ***	-0.0117 ***	17.83%	1.92%
2-5 years	-0.0206 ***	-0.0092 **	15.56%	1.68%
5-10 years	-0.0206 ***	-0.0060 *	12.73%	0.95%
10-30 years	-0.0107 ***	-0.0047	10.12%	0.33%
		Panel B: Liquidity Proxied by Quoted Depth		
		On-the-Run		
0-6 months	-0.0107 ***	-0.0065	10.24%	0.03%
6-12 months	-0.0218 ***	-0.0071 **	14.75%	0.95%
1-2 years	-0.0223 ***	-0.0080 **	20.93%	1.14%
2-5 years	-0.0224 ***	-0.0083 **	22.54%	1.17%
5-10 years	-0.0155 ***	-0.0072 **	18.84%	1.03%
10-30 years	-0.0181 ***	-0.0029	13.89%	0.47%

Figure 1: Change in the Yield of the 5-year Treasury Note

The left plot shows yield changes for the 5-year Treasury note on the three days surrounding the ten most influential macroeconomic announcements (civilian unemployment, consumer confidence, consumer prices, FOMC meetings, housing starts, industrial production, NAPM report, non-farm payroll, producer prices, and retail sales). The right plot shows the corresponding yield changes on all other days.

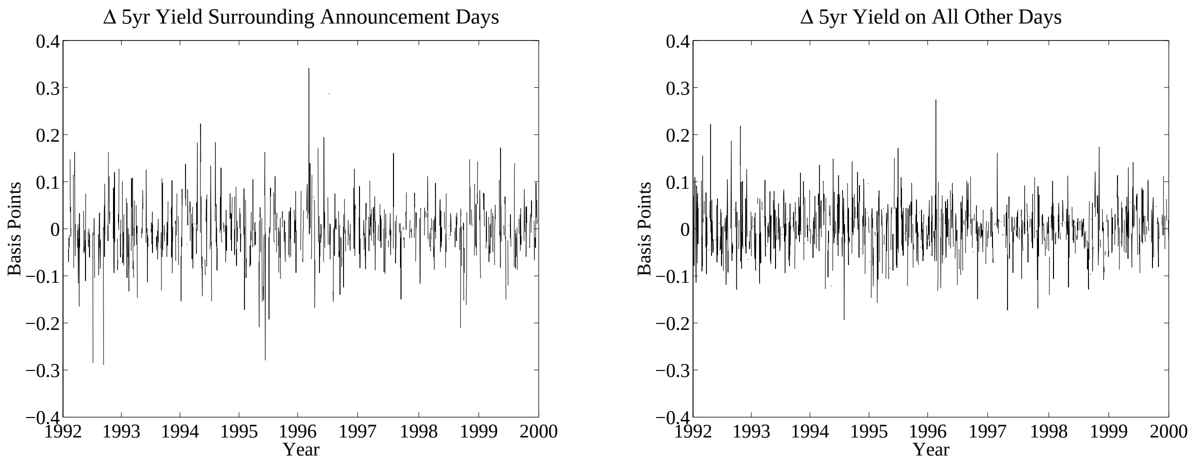


Figure 2: The Impact of Orderflow on the Yield Curve

The plots display the reaction of the yield curve to a one standard deviation net orderflow (purchases less sales) in each of the six issuing maturities. The black bars represent the unconditional reaction. The gray and white bars are for periods of high or low liquidity, respectively, where low liquidity is characterized as the bid-ask spread of the maturity in which the orderflow imbalance occurs being above its median.

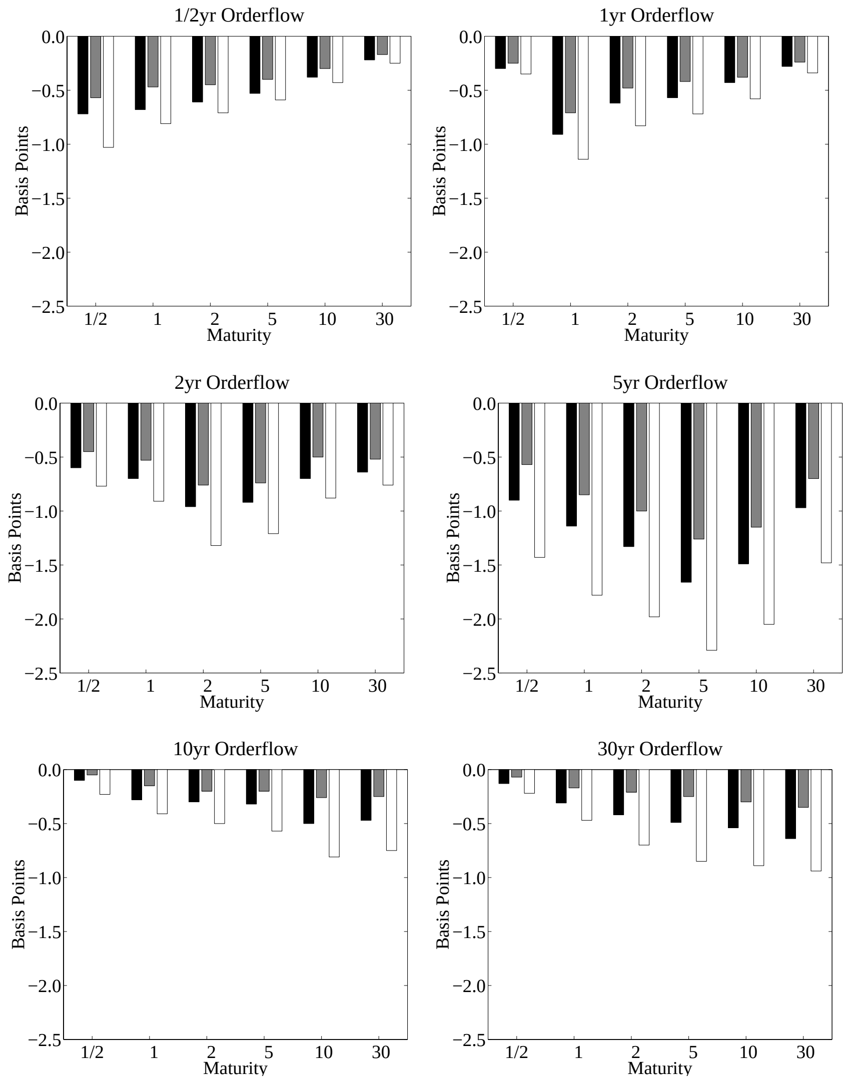


Figure 3: The Impact of Common Fixed Income Trading Strategies on the Yield Curve

The plots display the reaction of the yield curve to a five commond fixed income strategies (ladder, five-year bullet, five-year barbell, duration-neutral term spread, and duration-neutral and duration-weighted butterfly spread). Each strategy involved an absolute (buy and sell) orderflow of $100M. The black bars represent the unconditional reaction. The gray and white bars are for periods of high or low liquidity, respectively, where low liquidity is characterized as the bid-ask spread of the maturity in which the orderflow imbalance occurs being above its median.