Price Discovery in the U.S. Treasury Market: The Impact of Orderflow and Liquidity on the Yield Curve

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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) account for up to 26% 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 in understanding the behavior of the yield curve.

THE USE OF RISKLESS INTEREST RATES PERMEATES virtually every facet of economics and finance. It is therefore critical 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 date, 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 consensus is that more than one, but not many more than three factors capture the shape and day-to-day variation of the yield curve well. Although these factors are typically not uniquely identified, it is common to think of them 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. We conjecture that at least two complementary mechanisms are responsible for the day-to-day yield changes. First, yields are determined by public information flow, such as periodically scheduled macroeconomic announcements. Assuming that the basic structure of the economy and the interpretation of the announcement are common knowledge among all

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market participants, a release of public information about macroeconomic fundamentals results in an instantaneous adjustment of yields to new equilibrium levels. Subsequent trading in the Treasury market is strictly due to portfolio rebalancing and plays no role in determining bond yields. Empirically, there is overwhelming evidence in support of this public information flow mechanism in Fleming and Remolona (1997, 1999); Balduzzi, Elton, and Green (2001); and Green (2004). For example, Fleming and Remolona (1997) show that macroeconomic announcements are associated with the 25 largest price changes and most active trading periods in the bond market during their sample period. Acceptance of this mechanism is also growing among theorists, who have recently started incorporating announcements into term structure models (e.g., Piazzesi (2003)).

A second, less studied, mechanism for changes in the yield curve is the aggregation of heterogeneous private information (or heterogeneous interpretation of public information) through trading in the Treasury market. We label this mechanism *price discovery*. The basic framework is very similar to that described by Evans (2002) and Evans and Lyons (2002a) for currency markets.[1] Consider a set of Treasury market participants, each of whom has his own model for how the yield curve relates to economic fundamentals and about the current state of the economy given past public information releases. Some individuals or institutions may even have limited private information in the more traditional sense (e.g., a hedge fund with an ex-member of the Federal Reserve Board). With this incomplete and heterogeneous information structure, market participants are left to trade Treasury securities based on their subjective valuations. Since the market does not clear instantaneously, except by chance, participants can at the same time infer information about the subjective valuations of all other participants from the aggregate orderflow. This information may lead them to revise their subjective valuation. For instance, if at a posted price the buy orders at that price exceed the sell orders in aggregate, market participants with lower subjective valuations may decide to revise their valuations upward. Intuitively, the magnitude of the revision depends on how sure each participant is in his private models and/or information.

An empirical prediction of this second mechanism is that yield changes are not necessarily concentrated around the release of public information. Figure 1 provides casual support of this prediction. The plot shows the changes in the yield of the on-the-run, 5-year U.S. Treasury note on all days, except for the 3 days surrounding the 10 most influential macroeconomic announcements.[2] The standard deviation of the daily yield changes on nonannouncement days is 5.2 basis points, compared to the average bid-ask spread of about one basis point. Thus, the figure shows clearly that there is still substantial variation in yields, even in the absence of identifiable public information releases,

[1] See also Lyons (2001a, 2001b) and Evans and Lyons (2002b).

[2] The announcements pertain to civilian unemployment, consumer confidence, consumer prices, FOMC meetings, housing starts, industrial production, NAPM report, nonfarm payroll, producer prices, and retail sales. Eliminating the 3 days surrounding announcements is meant to be conservative since Jones, Lamont, and Lumsdaine (1998) document that the volatility surrounding announcements typically does not extend beyond a day.

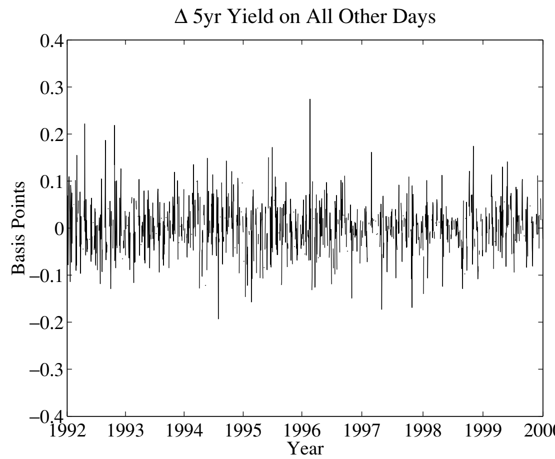

Figure 1. Change in the yield of the 5-year Treasury note. The plot shows yield changes for the 5-year Treasury note on all days of our sample except for the 3 surrounding the 10 most influential macroeconomic announcements (civilian unemployment, consumer confidence, consumer prices, FOMC meetings, housing starts, industrial production, NAPM report, nonfarm payroll, producer prices, and retail sales).

suggesting 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 goal of this paper is to further explore the role of price discovery in the U.S. Treasury market. We measure the response of yields to orderflow imbalances (i.e., excess buying or selling pressure) on days without major macroeconomic announcements, similar to Evans and Lyons (2002b) and Green (2004). We extend the analysis of Green (2004) to account for the varying seasonedness, time to maturity, and liquidity of the different Treasury securities. The reason for conditioning on seasonedness and time to maturity is that price discovery may not occur uniformly in all segments of the Treasury market. The intuition underlying the conditioning on liquidity is that when market participants are relatively certain about their private models and/or information, they are less concerned about trading with a better informed counterparty and hence are willing to provide more liquidity. Conditioning on liquidity therefore captures the notion that the extent to which yields respond to orderflow imbalances should depend on how much market participants trust in their private models and/or information.

Our empirical results strongly support the hypothesis that price discovery plays an important role in the U.S. Treasury market. We find that orderflow imbalances account for up to 26% 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 yields are permanent, at least over a 2-week period following the orderflow imbalance, and are not attributed to an inventory premium. Furthermore, we find that the relationship between yields and orderflow becomes even stronger when we condition our analysis on liquidity in the Treasury market. 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%. This finding is consistent with market participants paying more attention to orderflow when the subjective valuations are relatively uncertain (and liquidity is therefore low). Finally, we illustrate the multidimensional aspect and practical relevance of our results in the context of fixed income trading strategies.

Our work is related to a number of concurrent studies on orderflow in the U.S. Treasury market. Fleming (2001) examines various liquidity measures, including the response of yields to orderflow, and argues that yield changes in the absence of public information releases are due to inventory effects. By documenting that orderflow imbalances are associated with permanent, as opposed to transitory yield changes, our results contradict this inventory effect interpretation and instead point to price discovery as the underlying mechanism. Cohen and Shin (2003) employ a methodology similar to ours to examine feedback effects. They find that while orderflow imbalances have a significant impact on prices under normal conditions, during extremely volatile periods there is also a significant reverse impact of prices on orderflow imbalances. Finally, Green (2004) studies the information content of price changes of the 5-year Treasury note surrounding news releases and concludes, consistent with our findings, that trading subsequent to the announcements aids in price discovery.

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 yield curve dynamics. It follows that existing term structure models can benefit from a better understanding of the information structure and the way heterogeneous models and/or information are aggregated in the Treasury market. On a more fundamental level, our 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 analysis 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 intraday 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 interdealer Treasury securities brokers.[3] Fleming (1997) estimates that these five brokers account for approximately two-thirds of the interdealer broker market, which in turn represents roughly 45% of the trading volume in the secondary market for Treasury securities. Our sample period covers January 1992 through December 1999.

The GovPX data set contains security identifier information, including the CUSIP, coupon, and 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 contain 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 intraday frequency. Our data include 97.0 million records (89.9 million quotes and 7.1 million 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, nonfarm payroll, retail sales, industrial production, consumer confidence, and 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-maturity* of a security, which we split into six categories: 1 day to 6 months, 6–12 months, 12 months to 2 years, 2–5 years, 5–10 years, and 10–30 years.[4]

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 create 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

[3] GovPX covers the following interdealer brokers: Liberty, Tullett and Tokyo, and Garban, ICAP, and Hilliard Farber. Cantor Fitzgerald is the only major interdealer broker that is missing from the GovPX data set. 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.

[4] Each category is made wide enough to include the when-issued trading of the issuing-maturity security.

explicitly. Second, our partition is consistent with the repurchase agreement (repo) market, which is closely connected to the Treasury market, where rates are segmented into on-the-run, just off-the-run, and general collateral (i.e., all other securities). Technically, we make the distinction between the off-the-run bonds by counting the auctions of similar maturities that have 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 (6 time-to-maturity categories by 3 seasonedness categories). Notice that the 6 on-the-run categories correspond simply to the 6 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.).[5]

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 typically 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 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 both 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 a security's yield observation at date t to be included in the analysis, we require that security to have a yield observation at date t and at date $t + 1$. We use these two yield observations to compute the yield change for each security and then aggregate across these changes within each category. Computing aggregate yield changes this way results in a much less noisy series than simply computing the change in the aggregate yields using the unfiltered data. This is especially true for off-the-run securities for which the change in the aggregate yields is often driven by isolated transactions of two very different securities (with different seasonedness, coupons, or liquidity, for example).

[5] The just off-the-run categories have two securities each, except for the maturities under 6 months, which have four securities. The off-the-run categories have varied numbers of securities, with 61 for the shortest maturity category, 37 for the longest maturity category, and approximately 15 for all the other interim maturity categories.

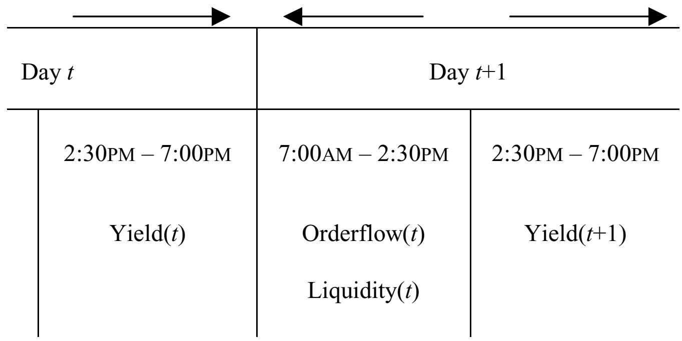

Figure 2. Diagram of variable measurement. The diagram show the periods of time during the day over which each of the variables of interest are measured.

Finally, we employ an intraday 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 nonsynchronous 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 (approximately 7:00 A.M. until 2:30 P.M.). In contrast, yields are averaged from 2:30 P.M. until the end of the trading day (approximately 7:00 P.M.). Aggregating the variables in this way measures orderflow and liquidity during the active trading period and provides orderflow every opportunity to affect yields without the potential confounding effects of nonsynchronous movements in the variables. Figure 2 illustrates this sampling scheme.

C. Summary Statistics and Factor Structures

Table I provides basic summary statistics for the yields, net orderflow, bid-ask spreads, and quoted depth in our sample. The average yields display the usual upward sloping nature of the yield curve. Net orderflow tends to be positive on average, signifying net purchases. The standard deviations are very large, revealing substantial variation and potential for large negative net orderflow. 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.

The correlations of these variables (not shown to preserve space) reveal that the yields are strongly positively correlated across the time-to-maturity and

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 data set. 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 ($million)						
On-the-run	22.443 [322.111]	−52.082 [372.891]	246.909 [594.361]	307.857 [604.659]	144.651 [343.624]	22.884 [121.397]
Just off-the-run	12.250 [145.323]	−6.662 [110.529]	29.838 [115.934]	21.797 [89.382]	7.555 [46.129]	4.494 [39.263]
Off-the-run	29.945 [3871.440]	67.652 [228.883]	86.873 [250.132]	52.243 [138.983]	5.371 [54.497]	0.958 [20.840]
Bid-ask spreads (% of midpoint price)						
On-the-run	0.033 [0.017]	0.056 [0.029]	0.075 [0.030]	0.129 [0.043]	0.235 [0.066]	0.553 [0.153]
Just off-the-run	0.067 [0.052]	0.138 [0.079]	0.209 [0.097]	0.350 [0.119]	0.605 [0.149]	0.646 [0.211]
Off-the-run	0.123 [0.049]	0.210 [0.077]	0.329 [0.105]	0.508 [0.148]	0.736 [0.203]	0.740 [0.214]
Quoted depth ($million)						
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]

seasonedness categories (correlations ranging from 0.25 to 0.99 with a median of 0.81). Net orderflow and the liquidity variables are each relatively less correlated. For net orderflow, the median correlation is 0.10 in the time-to-maturity dimension (ranging from −0.04 to 0.32) and 0.15 in the seasonedness dimension (ranging from 0.05 to 0.27). For the liquidity variables, the corresponding median correlations are 0.30 (ranging from 0.04 to 0.73) and 0.41 (ranging from 0.11 to 0.66), respectively. The correlations of net orderflow with the liquidity variables are even smaller in magnitude, with a median of 0.01 and a range of −0.11 to 0.17. Finally, the yields and liquidity variables are highly autocorrelated, while net orderflow appears virtually independent through time (consistent with news arrival being independent).

To get a better sense for the multivariate structure of the data across the time-to-maturity categories in a given seasonedness category, which is how the term structure literature tends to look at the data, we perform standard factor decompositions. In particular, we use principal 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 A and B are matrices of constants and factor loadings, respectively. We let $X(t)$ be the (6×1) vector of yields, net orderflow, bid-ask spreads, or quoted depth within a given seasonedness category.[6]

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 1% of the variation in yields, respectively. The first factor, commonly called the level factor, loads about equally on all maturities, with a slight emphasis on the 1–5-year range. The second factor loads positively on long and negatively on short maturities and is hence labeled the slope factor. The third factor, often called the curvature factor, loads positively on long and short maturities and negatively on medium maturities.

Although it is plausible that the same three factors explain the variation in the on-the-run net orderflow and liquidity variables, 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% of the variation. This factor loads about equally on the net orderflow of all bonds, with a slight emphasis of the 2–5-year maturities. The remaining five factors explain approximately equal amounts of the variation of net orderflow, ranging from 16 to 11%. 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

[6] The results are not sensitive to whether the factors are constructed from yields or changes in yields as has been done in much of the previous literature. Furthermore, the results are not changed by using likelihood-based factor analysis instead of principal components to extract the common factors.

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	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	6^{th}
Yields						
0–6 months	0.396	−0.436	0.640	0.293	0.390	0.079
6–12 months	0.423	−0.369	0.082	−0.271	−0.707	−0.323
1–2 years	0.464	−0.179	−0.427	−0.337	0.150	0.659
2–5 years	0.472	0.118	−0.435	0.102	0.416	−0.625
5–10 years	0.389	0.460	−0.027	0.655	−0.378	0.254
10–30 years	0.275	0.645	0.459	−0.537	0.094	−0.016
% explained	0.727	0.265	0.006	0.001	0.001	0.000
Net orderflow						
0–6 months	0.320	−0.535	0.733	−0.146	−0.232	0.017
6–12 months	0.400	−0.199	−0.140	0.874	0.032	0.126
1–2 years	0.435	−0.309	−0.403	−0.420	0.341	0.510
2–5 years	0.517	−0.002	−0.204	−0.158	0.112	−0.808
5–10 years	0.409	0.424	−0.137	−0.115	−0.759	0.213
10–30 years	0.337	0.631	0.470	0.024	0.491	0.159
% explained	0.324	0.160	0.145	0.136	0.129	0.1057
Bid-ask spreads						
0–6 months	0.368	−0.216	0.691	0.578	0.080	−0.018
6–12 months	0.407	−0.003	0.451	−0.779	−0.133	0.086
1–2 years	0.435	0.441	−0.197	0.049	0.635	0.415
2–5 years	0.492	0.115	−0.259	0.009	0.040	−0.822
5–10 years	0.470	0.043	−0.327	0.216	−0.704	0.358
10–30 years	0.218	−0.863	−0.326	−0.105	0.275	0.125
% explained	0.561	0.165	0.117	0.081	0.045	0.031
Quoted depth						
0–6 months	0.268	0.180	−0.811	−0.482	0.070	−0.027
6–12 months	0.372	0.215	−0.312	0.834	0.149	0.012
1–2 years	0.527	−0.008	0.193	−0.066	−0.475	−0.675
2–5 years	0.528	−0.137	0.141	−0.090	−0.379	0.729
5–10 years	0.481	−0.200	0.297	−0.190	0.775	−0.064
10–30 years	−0.048	−0.929	−0.316	0.154	−0.059	−0.091
% explained	0.471	0.171	0.154	0.111	0.055	0.038

and depth contain a predominant common factor, explaining between 47 and 56% of the variation in spreads and depth, while the remaining five factors explain between 3 and 17%, respectively. 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 1% 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 nontrivial 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, and the liquidity variables are different. We use these results to guide our modeling choices in the following sections.

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 a first-order VAR as a baseline model for the daily dynamics of yields. 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.[7] 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%, 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.

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

[7] 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 are interpolated.

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. The symbols *, **, and *** 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	0.381***	−0.431***	0.621***	0.051	99.70%	1.09%
6–12 months	0.440***	−0.383***	0.067***	0.067	99.50%	0.61%
1–2 years	0.472***	−0.175***	−0.439***	0.058	99.57%	0.46%
2–5 years	0.452***	0.119***	−0.427***	0.060	99.44%	0.41%
5–10 years	0.386***	0.453***	−0.063***	0.068	99.28%	0.55%
10–30 years	0.281***	0.646***	0.461***	0.051	99.60%	0.64%
Just off-the-run						
0–6 months	0.391***	−0.425***	0.594***	0.058	99.59%	0.53%
6–12 months	0.424***	−0.389***	0.134***	0.064	99.53%	0.51%
1–2 years	0.453***	−0.211***	−0.383***	0.083	99.14%	0.34%
2–5 years	0.437***	0.078***	−0.634***	0.074	99.15%	0.18%
5–10 years	0.400***	0.468***	0.069***	0.084	98.72%	0.29%
10–30 years	0.321***	0.633***	0.356***	0.064	98.95%	0.42%
Off-the-run						
0–6 months	0.402***	−0.550***	0.557***	0.054	99.66%	0.73%
6–12 months	0.412***	−0.419***	−0.039***	0.053	99.69%	0.59%
1–2 years	0.417***	−0.194***	−0.546***	0.072	99.37%	0.52%
2–5 years	0.409***	0.242***	−0.517***	0.072	99.16%	0.44%
5–10 years	0.413***	0.434***	0.052***	0.096	98.55%	0.58%
10–30 years	0.385***	0.485***	0.609***	0.080	98.86%	0.69%

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.

B. 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 Figure 2).

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 3 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).[8] Focusing on the remaining nonannouncement 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, which 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) explained by net orderflow. In all cases, these incremental R^2 are substantial, ranging from 5 to 25%.

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

[8] We also conducted the analysis eliminating only the announcement day for the entire set of macro announcements listed in footnote 2. The results are qualitatively and quantitatively the same. The tables are available on request.

[9] These results are consistent with Fleming (2001).

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 nonannouncement 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. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Net Orderflow by Maturity (×100)											
Maturity	0–6 months	6–12 months	1–2 years	2–5 years	5–10 years	10–30 years	Res Std	Adj R^2	All Days Adj R^2	1st Net Orderflow Factor (×100)	Res Std	Adj R^2
On-the-run												
0–6 months	−0.72***	−0.30**	−0.60***	−0.90***	−0.10	−0.13	0.044	10.61%	9.57%	−1.47***	0.054	10.21%
6–12 months	−0.50***	−0.91***	−0.70***	−1.14***	−0.28	−0.31***	0.060	15.37%	13.51%	−2.29***	0.060	13.80%
1–2 years	−0.61***	−0.62***	−0.96***	−1.33***	−0.30*	−0.42***	0.048	21.15%	18.83%	−2.48***	0.048	19.79%
2–5 years	−0.68***	−0.57***	−0.92***	−1.66***	−0.32**	−0.49***	0.050	24.67%	20.19%	−2.63***	0.050	21.37%
5–10 years	−0.38***	−0.43***	−0.70***	−1.49***	−0.50**	−0.54***	0.059	19.15%	17.61%	−2.78***	0.059	17.81%
10–30 years	−0.22	−0.28**	−0.64***	−0.97***	−0.47***	−0.64***	0.046	15.58%	12.31%	−1.65***	0.046	13.42%
Just off-the-run												
0–6 months	−0.56***	−0.47***	−0.55***	−0.83**	−0.28	0.04	0.054	4.68%	3.51%	−0.91***	0.054	3.62%
6–12 months	−0.41***	−0.88***	−0.69***	−1.16***	−0.35*	−0.56***	0.057	15.10%	14.93%	−2.36***	0.057	14.78%
1–2 years	−0.43**	−0.86***	−0.95***	−1.40***	−0.45*	−0.61***	0.073	16.00%	13.65%	−3.04***	0.073	14.85%
2–5 years	−0.59***	−0.81***	−1.04***	−1.84***	−0.52**	−0.46**	0.062	17.37%	15.94%	−2.73***	0.062	16.34%
5–10 years	−0.91***	−0.77***	−0.98***	−1.31***	−0.75***	−0.39**	0.074	15.69%	14.30%	−2.34***	0.074	14.46%
10–30 years	0.00	−0.57**	−0.57*	−0.94***	−0.53**	−0.33*	0.055	16.07%	15.70%	−2.31***	0.055	15.25%
Off-the-run												
0–6 months	−0.51***	−0.43***	−0.29*	−0.36**	−0.02	−0.16	0.048	5.09%	4.40%	−0.99***	0.048	4.72%
6–12 months	−0.44***	−0.72***	−0.68***	−0.74***	−0.27*	−0.63	0.043	16.45%	16.19%	−1.93***	0.043	15.42%
1–2 years	−0.54***	−0.65***	−0.96***	−1.37***	−0.35**	−0.37*	0.061	16.33%	14.27%	−2.83***	0.061	15.91%
2–5 years	−0.50***	−0.56***	−0.82***	−1.68***	−0.38**	−0.64*	0.061	14.53%	13.81%	−2.52***	0.062	13.88%
5–10 years	−0.64**	−0.42***	−1.00***	−1.20**	−0.43***	−0.79**	0.086	13.41%	12.97%	−2.40***	0.086	11.78%
10–30 years	0.84	−0.35	−2.00***	−0.50	−0.24**	−0.81**	0.071	12.60%	11.39%	−2.70***	0.075	9.79%

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 its own orderflow imbalance, relative to adjacent maturity ranges, but an even stronger reaction to the orderflow imbalance at the 2–5-year maturity range. The prominence of this maturity range may be institutional because the majority of fixed income portfolios are likely to have a duration near 5 years (the middle of the yield curve). Futures trading is concentrated in the 5-year note, which is consistent with the 5-year future being used as a hedge instrument. The relative importance of the 2–5-year maturity range may therefore be a product of it containing a bellwether security that is universally held and used for hedging.

Another interesting result is that the incremental R^2 are highest for the 2–5-year range and decrease monotonically for shorter and longer maturities. This pattern is the exact *opposite* of 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 nonannouncement 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 for just nonannouncement 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 nonannouncement days sample. Specifically, the incremental R^2 for all days (also shown in Table IV) are as much as 4.5% smaller than for the nonannouncement days.

Using a dummy variables approach, we further examine whether the effect of orderflow imbalances on yields is different for announcement and nonannouncement days. The results, which are omitted from the table, show that the effect is remarkably stable across the two subsamples. Consistent with our reasoning above that announcements lead to instantaneous yield changes with balanced orderflow, the only difference between announcement and nonannouncement days is that on announcement days, yields change primarily without concurrent orderflow imbalances. This causes the estimates of the net orderflow coefficients to be noisier and also explains why the all-days incremental R^2 are lower.

Finally, recall from the factor analyses in Table II that net orderflow contains a common factor that accounts for about 32% 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 nonannouncement 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%) 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 2–5-year range) is associated with 1–10-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 not 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% 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 next examine 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%. 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 8 and 5% 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

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 nonannouncement days and include intercepts and coefficients on the yield factors at date $t-1$ that are not tabulated. 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 results of regressing the yield factors on the first net orderflow factor. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Net Orderflow by Maturity (×100)										
Factors	0–6 months	6–12 months	1–2 years	2–5 years	5–10 years	10–30 years	Res Std	Adj R^2	1st Net Orderflow Factor (×100)	Res Std	Adj R^2
Level	−1.21***	−1.57***	−1.84***	−2.86***	−0.70**	−1.00***	0.086	28.14%	−5.50***	0.087	27.68%
Slope	0.18	−0.10	−0.22*	−0.51***	−0.33***	−0.10	0.035	8.27%	−0.71***	0.035	7.67%
Curvature	0.03	0.16**	0.14**	0.29***	−0.06	0.07	0.020	4.95%	0.42***	0.020	3.77%

due to the loadings of the slope and curvature factors not summing to zero.[10] For example, if net orderflow explains 28% 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 6% 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% 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]

C. Price Discovery or Inventory 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-adverse 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 such an 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 5-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 the 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 future markets (e.g., Garbade and Silber (1979, 1983))

[10] Suppose the yield curve is flat at 8% 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.

suggest that price discovery where substitutes are present tends to take place in the market that is most liquid. Inventory premiums, on the contrary, are by definition more prevalent in illiquid markets. To differentiate between price discovery and inventory premiums, we therefore 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 inventory 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 orderflow coefficients are almost all insignificantly different from zero, suggesting that own net orderflow contains no information in addition to on-the-run net orderflow.[12]

While the first two pieces of evidence support the price discovery hypothesis, we acknowledge that it does not completely rule out an inventory explanation, particularly if Treasury dealers manage inventory using a duration metric, as in Naik and Yadav (2003). Our third piece of evidence provides the strongest support for the price discovery hypothesis. Specifically, we exploit the different intertemporal predictions of the two hypotheses. While the impact of price discovery on yields is permanent, the inventory 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 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 1-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 10% of the coefficients are statistically different from zero at the 10% level (which is consistent with the null of zero coefficients at

[12] The off-the-run 10–30-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.

[13] Our 1 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 details on these statistics see, www.ustreas.gov and www.publicdebt.treas.gov.

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 nonannouncement 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 measures 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. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Own Net Orderflow by Maturity (×100)						On-the-run Net Orderflow by Maturity (×100)							
Maturity	0–6 months	6–12 months	1–2 years	2–5 years	5–10 years	10–30 years	0–6 months	6–12 months	1–2 years	2–5 years	5–10 years	10–30 years	Adj R^2	ΔAdj R^2
Just off-the-run														
0–6 months	−0.13	−0.04	−0.06	−0.03	−0.02	0.46*	−0.21***	−0.37***	−0.69**	0.43**	−0.28	−0.30	5.03%	0.35%
6–12 months	−0.80*	0.15	−0.16	0.08	−0.04	0.15	−0.15**	−0.56***	−0.47***	−1.08***	−0.54	−0.34	15.28%	0.18%
1–2 years	−0.42	0.00	−0.31	−0.04	−0.46*	−0.64*	−0.61**	−0.52**	−0.99***	−1.77***	−0.98**	−0.45*	15.98%	−0.02%
2–5 years	−0.70	−0.01	−0.59	0.33	0.11	−0.02	−0.42**	−0.40**	−0.82**	−1.32**	−1.25***	−0.72**	17.32%	−0.05%
5–10 years	0.25	−0.10	−0.59	−0.35	−0.33	−0.40	−0.93**	−0.32	−0.57	−1.00***	−1.46***	−1.08**	15.69%	0.00%
10–30 years	−0.24	0.37*	−0.55	0.21	0.02	−0.03	−0.02	−0.55*	−0.33	−1.39**	−1.09***	−1.13***	16.33%	0.26%
Off-the-run														
0–6 months	−1.42	−1.01	−0.11	−0.01	−0.52	0.65	−0.25***	−0.59**	−0.16	−0.79	−0.32	−0.29**	5.44%	0.35%
6–12 months	0.15	−1.56	−0.67	0.04	−0.76*	0.68*	−0.53**	−0.31***	−0.61**	−0.81**	−0.17	−0.69*	16.64%	0.19%
1–2 years	1.51*	−0.60	−0.64*	0.11	−0.53	−0.17	−0.17**	−0.38***	−0.79***	−1.34**	−0.83	−0.81*	16.37%	0.04%
2–5 years	−2.76*	−1.62*	−0.31	−0.92*	−0.54	0.96*	−0.72*	−0.24*	−0.13**	−1.36***	−1.06*	−0.96**	14.52%	−0.01%
5–10 years	1.88*	−2.89*	−0.40	0.07	−0.84*	0.32	−0.14	−0.90	−0.76	−1.14**	−1.46**	−1.04***	13.48%	0.07%
10–30 years	−0.68	0.30	−0.05	−0.26	−0.31	−1.27*	−1.17	−0.40	−0.65	−1.07**	−1.83**	−1.25**	12.71%	0.11%

Table VII

Response of Yields to Contemporaneous and 1-Day 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 nonannouncement 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. ΔAdj R^2 denotes the change in the adjusted R^2 relative to the results in Table IV. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Contemporaneous Net Orderflow by Maturity (×100)						One-Day Lagged Net Orderflow by Maturity (×100)							
Maturities	0–6 months	6–12 months	1–2 years	2–5 years	5–10 years	10–30 years	0–6 months	6–12 months	1–2 years	2–5 years	5–10 years	10–30 years	Adj R^2	ΔAdj R^2
On-the-run														
0–6 months	-0.65^{***}	-0.41^{**}	-0.54^{***}	-0.61^{***}	−0.07	−0.13	0.08	−0.11	−0.03	−0.09	0.09	−0.19	10.06%	−0.55%
6–12 months	-0.55^{***}	-1.02^{***}	-0.66^{***}	-0.97^{***}	−0.22	-0.65^{***}	0.22	-0.38^{*}	−0.30	−0.15	−0.08	−0.29	15.68%	0.31%
1–2 years	-0.62^{***}	-0.72^{***}	-0.95^{***}	-1.10^{***}	-0.22^{**}	-0.47^{***}	0.27	−0.09	-0.29^{*}	−0.07	−0.12	-0.52^{*}	21.38%	0.23%
2–5 years	-0.68^{***}	-0.79^{***}	-1.02^{***}	-1.22^{***}	-0.29^{**}	-0.38^{**}	0.15	−0.17	−0.21	−0.19	0.03	-0.45^{*}	25.18%	0.51%
5–10 years	-0.44^{**}	-0.97^{***}	-0.67^{***}	-1.54^{***}	-0.22^{***}	-0.43^{**}	0.11	-0.57^{*}	−0.16	-0.55^{*}	−0.17	−0.20	19.85%	0.70%
10–30 years	−0.19	-0.45^{**}	-0.64^{***}	-0.66^{***}	-0.43^{***}	-0.38^{**}	0.30^{*}	−0.04	−0.28	−0.03	−0.05	-0.25^{*}	15.96%	0.38%
Just off-the-run														
0–6 months	-0.51^{***}	-0.58^{***}	-0.59^{***}	-0.18^{*}	0.25	0.08	−0.22	−0.07	0.18	0.54	0.17	0.10^{*}	5.36%	0.68%
6–12 months	-0.44^{***}	-1.02^{***}	-0.68^{***}	-1.02^{***}	-0.29^{***}	-0.63^{***}	0.19	−0.35	−0.25	−0.13	−0.21	-0.30^{*}	15.78%	0.68%
1–2 years	-0.59^{***}	-0.80^{***}	-0.87^{***}	-1.75^{***}	-0.48^{***}	-0.66^{**}	0.76	−0.36	-0.24^{*}	−0.73	0.07	−0.46	17.16%	1.16%
2–5 years	-0.57^{***}	-0.86^{***}	-1.19^{***}	-1.16^{***}	-0.28^{**}	-0.37^{**}	−0.07	-0.02^{*}	−0.41	0.34	−0.28	−0.22	17.14%	−0.23%
5–10 years	-0.98^{***}	-0.90^{***}	-0.77^{***}	-0.95^{***}	-0.45^{**}	-0.32^{**}	0.28	−0.94	−0.14	−0.22	0.68	−0.23	15.46%	−0.23%
10–30 years	0.11	-0.51^{**}	-0.63^{*}	-0.71^{**}	-0.98^{*}	-0.39^{**}	0.00	0.29	−0.47	−0.46	−0.23	−0.32	14.12%	−1.95%
Off-the-run														
0–6 months	-0.51^{***}	-0.34^{**}	-0.34^{*}	-0.32^{*}	−0.09	−0.10	0.02	−0.31	−0.17	0.36	0.03	−0.17	4.78%	−0.31%
6–12 months	-0.44^{***}	-0.79^{***}	-0.70^{***}	-0.68^{***}	-0.30^{**}	−0.59	−0.03	−0.16	−0.08	0.05	−0.10	−0.27	16.94%	0.49%
1–2 years	-0.47^{***}	-0.81^{***}	-0.89^{***}	-1.51^{***}	-0.26^{**}	−0.34	0.17	−0.16	−0.32	−0.46	−0.24	−0.23	16.07%	−0.26%
2–5 years	-0.54^{***}	-0.66^{***}	-1.00^{***}	-1.29^{***}	-0.34^{***}	-0.53^{**}	0.30	−0.09	−0.05	−0.10	0.00	−0.58	15.28%	0.75%
5–10 years	-0.72^{**}	-0.55^{***}	-1.01^{***}	-0.51^{**}	-0.45^{***}	-0.60^{**}	0.21	−1.15	−0.19	0.42	0.21	−0.09	12.55%	−0.86%
10–30 years	1.00	-0.35^{**}	-2.51^{***}	−0.28	-0.21^{***}	-0.88^{**}	0.40	0.46	0.32	−0.32	−1.36	−0.47	11.57%	−1.03%

that significance level). The adjusted incremental R^2 increases only marginally (in some cases even decreases) relative to the results in Table IV.

To address the possibility of more gradual reversals, we also include further lagged net orderflows. Table VIII presents the results from regressing yield change on contemporaneous and up to 5-day lagged realizations of the first net orderflow factor. For reference, the table also repeats the results from including only contemporaneous orderflow, shown originally in the last three columns of Table IV. Judging by the coefficients on lagged net orderflow, there is again no sign of a systematic positive correlation at any lag ranging from 1 day to 1 week. There is a slight negative 1-day lagged correlation caused by a modest amount of persistence in the net orderflow factor, but the coefficients are all an order of magnitude smaller than the contemporaneous effect, and the adjusted incremental R^2 is virtually unchanged. As a final robustness check, we repeat this analysis with individual maturity net orderflows lagged up to 2 weeks. The results are qualitatively identical to those in Table VIII.

Considering the three pieces of evidence together, we are confident that the yield changes associated with orderflow imbalances are *not* attributed to 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 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. Finally, we now standardize net orderflow by its *conditional* standard deviation for the below or above median liquidity subsamples. The reason for doing so is to eliminate the effect of the rather strong correlation between the magnitude of net orderflow and liquidity. Intuitively, a certain orderflow imbalance is likely to be more

Table VIII

Response of Yields to Contemporaneous and Lagged Orderflow Factor

This table presents the results of regressing yields of six maturity categories at date t on the first net orderflow (purchases less sales) factor between dates $t-1$ and t as well as up to 5-day lagged values of the net orderflow factor. The regressions are for nonannouncement 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. ΔAdj R^2 denotes the change in the adjusted R^2 from including the lagged net orderflow factor. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

Maturity	1st Net Orderflow Factor (×100)	Res Std	Adj R^2	1st Net Orderflow Factor (×100): Contemporaneous	1-Day Lagged	2-Day Lagged	3-Day Lagged	4-Day Lagged	5-Day Lagged	Res Std	Adj R^2	ΔAdj R^2
On-the-run												
0–6 months	−1.47***	0.054	10.21%	−1.37***	0.06	0.07	0.00	0.01	0.05	0.054	8.15%	−2.06%
6–12 months	−2.29***	0.060	13.80%	−2.13***	−0.13*	−0.02	−0.09	−0.01	0.00	0.058	11.10%	−2.70%
1–2 years	−2.48***	0.048	19.79%	−2.52***	−0.15*	0.06	−0.00	0.04	0.05	0.047	19.72%	−0.07%
2–5 years	−2.63***	0.050	21.37%	−2.77***	−0.22**	−0.07	0.04	0.06	0.04	0.049	21.70%	0.33%
5–10 years	−2.78***	0.059	17.81%	−2.66***	−0.32**	0.05	0.00	0.01	−0.05	0.058	18.35%	0.54%
10–30 years	−1.65***	0.046	13.42%	−1.82***	−0.31**	0.03	−0.01	−0.00	0.01	0.046	13.95%	0.53%
Just off-the-run												
0–6 months	−0.91***	0.054	3.62%	−0.89***	0.11	0.03	−0.02	0.11	0.05	0.053	3.50%	−0.12%
6–12 months	−2.36***	0.057	14.78%	−2.29***	−0.09*	0.05	−0.08	0.01	−0.05	0.057	13.50%	−1.28%
1–2 years	−3.04***	0.073	14.85%	−3.07***	−0.21**	−0.06	−0.04	−0.04	0.02	0.073	15.25%	0.40%
2–5 years	−2.73***	0.062	16.34%	−2.79***	−0.19**	0.03	0.02	0.08	0.01	0.061	16.77%	0.43%
5–10 years	−2.34***	0.074	14.46%	−2.13***	−0.02	0.07	0.00	−0.04	0.06	0.074	13.43%	−1.03%
10–30 years	−2.31***	0.055	15.25%	−2.19***	−0.24*	−0.04	−0.02	0.00	−0.13	0.055	14.81%	−0.44%
Off-the-run												
0–6 months	−0.99***	0.048	4.72%	−0.75***	0.03	0.06	−0.03	0.05	0.09	0.048	4.68%	−0.04%
6–12 months	−1.93***	0.043	15.42%	−1.66***	−0.18*	0.04	−0.05	0.04	−0.03	0.042	14.42%	−1.00%
1–2 years	−2.83***	0.061	15.91%	−2.29***	−0.21**	0.03	−0.07	−0.01	−0.01	0.060	16.13%	0.22%
2–5 years	−2.52***	0.062	13.88%	−2.34***	−0.30**	0.04	0.01	0.10	0.01	0.060	15.02%	1.14%
5–10 years	−2.40***	0.086	11.78%	−2.21***	0.05	−0.10	−0.06	−0.06	0.03	0.085	10.23%	−1.55%
10–30 years	−2.70***	0.075	9.79%	−2.40***	−0.19**	−0.17*	−0.13*	−0.12*	−0.15*	0.073	11.33%	1.54%

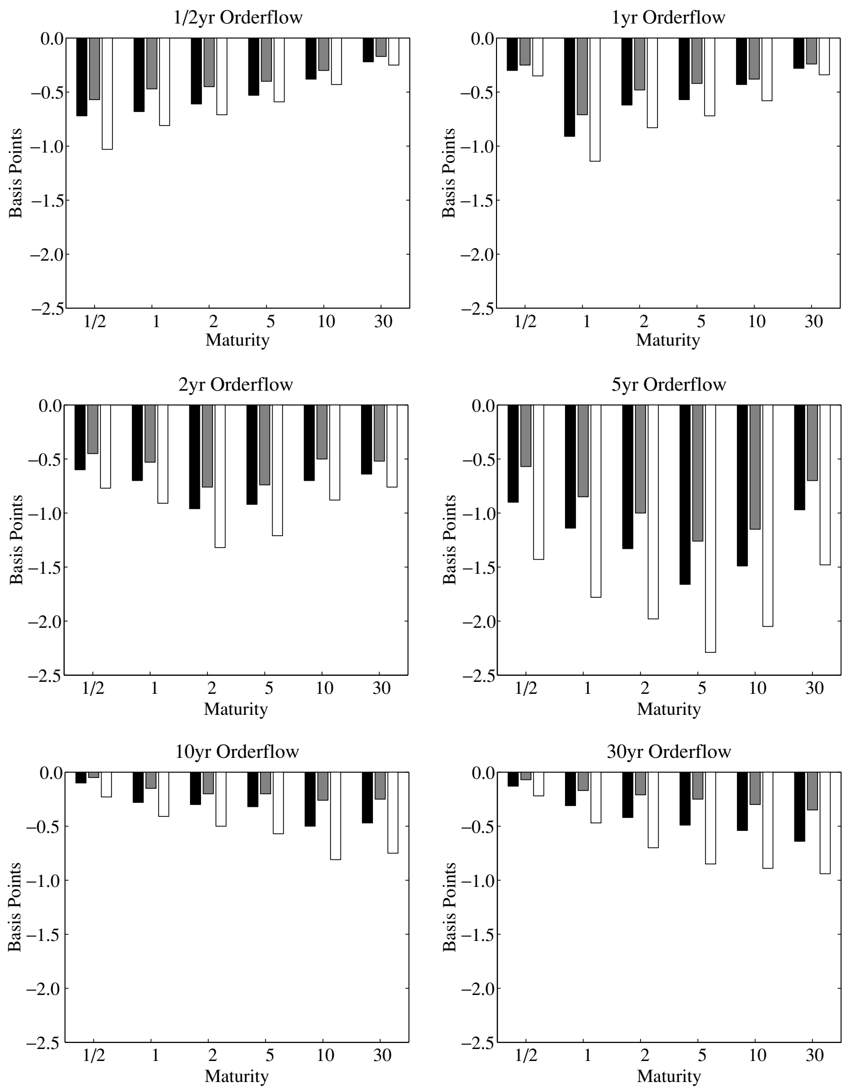

Figure 3. The impact of orderflow on the yield curve. The plots display the reaction of the yield curve to a one standard deviation net orderflow (purchases less sales) in each of the six issuing maturities. The black bars represent the unconditional reaction. The gray and white bars are for periods 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.

substantial under low liquidity than it is under high liquidity, when larger orderflow imbalances are more common.

Figure 3 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% greater than unconditionally and between 39 and 241% greater than during high liquidity. Third, despite the differences in magnitude, the general shape of the reaction along the yield curve is similar 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 (2- and 5-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 (10-year note and 30-year bond) tends to flatten the curve and has the smallest effect in magnitude, especially for the 10-year note.

To get a sense for the statistical significance of the interaction between orderflow and liquidity, we present in Table IX 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

[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.

Table IX

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 nonannouncement 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. ΔAdj R^2 denotes the change in the adjusted R^2 relative to the results in Table IV. The symbols *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	1st Net Orderflow Factor (×100)			
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	−1.02***	−0.77**	12.47%	2.26%
6–12 months	−1.77***	−0.93***	16.93%	3.13%
1–2 years	−1.89***	−1.07***	24.84%	5.05%
2–5 years	−2.08***	−1.17***	26.34%	4.97%
5–10 years	−2.09***	−1.30***	21.40%	3.59%
10–30 years	−1.50***	−0.42*	16.15%	2.73%
Just off-the-run				
0–6 months	−0.74***	−0.41*	4.65%	1.03%
6–12 months	−1.86***	−1.18***	16.96%	2.18%
1–2 years	−2.51***	−1.22***	17.34%	2.49%
2–5 years	−2.17***	−1.31***	19.15%	2.81%
5–10 years	−2.04***	−0.96**	16.51%	2.05%
10–30 years	−2.06***	−0.70*	16.37%	1.12%
Off-the-run				
0–6 months	−0.62***	−0.61*	4.79%	0.07%
6–12 months	−1.49***	−0.87**	16.96%	1.54%
1–2 years	−2.26***	−1.17***	17.83%	1.92%
2–5 years	−2.06***	−0.92**	15.56%	1.68%
5–10 years	−2.06***	−0.60*	12.73%	0.95%
10–30 years	−1.07***	−0.47	10.12%	0.33%
Panel B: Liquidity Proxied by Quoted Depth				
On-the-run				
0–6 months	−1.07***	−0.65	10.24%	0.03%
6–12 months	−2.18***	−0.71**	14.75%	0.95%
1–2 years	−2.23***	−0.80**	20.93%	1.14%
2–5 years	−2.24***	−0.83**	22.54%	1.17%
5–10 years	−1.55***	−0.72**	18.84%	1.03%
10–30 years	−1.81***	−0.29	13.89%	0.47%

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 5% level (in 16 of 24 cases), suggesting that the difference between the high- and low-liquidity coefficients is indeed nonzero. In relative terms, the low-liquidity coefficients are between 29 and 98% 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 (2 to 5%). 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 3 and Table IX 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 substantially update 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 3, 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 multidimensional relationship between yields, orderflow, and liquidity is therefore to examine the way yields change in response to these trading strategies.[15]

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

[15] Alternatively, one can interpret the results in this section as providing information about which trading strategies informed individuals or institutions are more likely to use. We thank the referee for this observation.

(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 3 can be interpreted in the context of bullets); (iii) a barbell—an investment in two nonadjacent 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 5-year bond, we center all trades at the 5-year maturity. We consider a 5-year bullet, a barbell with the duration of a 5-year bullet involving the 2 and 10-year maturities; a term spread with the 2- and 10-year maturities; and a butterfly spread with the 2-, 5-, and 10-year maturities. Finally, we set the absolute (long and short) orderflow to be \$100 million, which represents a fraction of the *hourly* volume in on-the-run securities and is not uncommon for large market participants.[16]

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 4 presents the results in the same format as Figure 3 (i.e., the black, white, and gray bars are the unconditional, low-, and high-liquidity responses, respectively), except with a different scale on the y-axis. Consider first the ladder, 5-year bullet, and 5-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 5-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 (1 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.

[16] More specifically, the five trading strategies involve the following positions: (i) ladder—long \$16.67 million in each of the 6-month and 1-year bills; 2-, 5-, and 10-year notes; and 30-year bond; (ii) bullet—long \$100 million in the 5-year note; (iii) barbell—long \$54.9 million in the 2-year note and \$45.1 million in the 10-year note; (iv) term spread—short \$80.4 million in the 2-year note and long \$19.6 million in the 10-year note; and (v) butterfly spread—long \$48.1 million and \$11.7 million in the 2- and 10-year notes, respectively, and short \$40.2 million in the 5-year note.

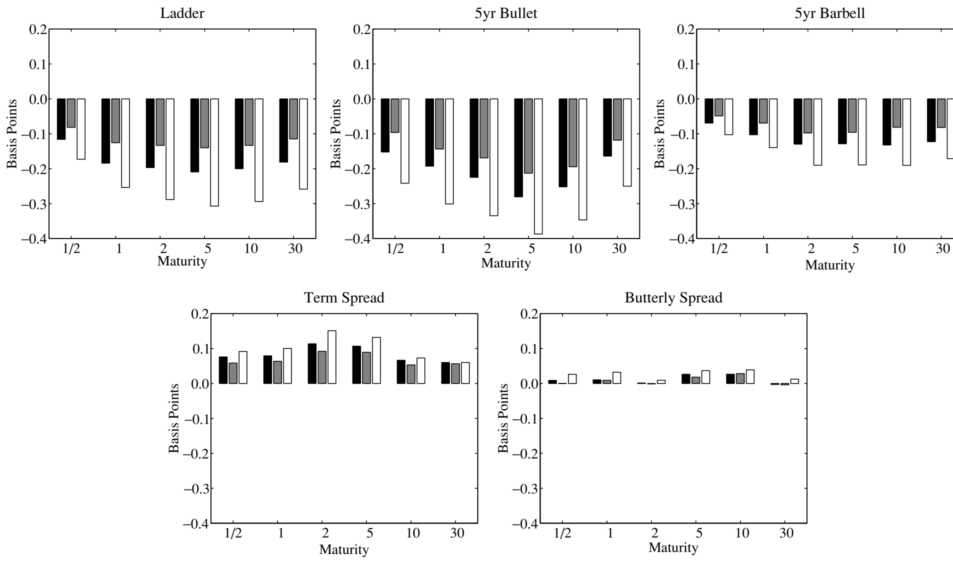

Figure 4. The impact of common fixed income trading strategies on the yield curve. The plots display the reaction of the yield curve to a five common fixed income strategies (ladder, 5-year bullet, 5-year barbell, duration-neutral term spread, and duration-neutral and duration-weighted butterfly spread). Each strategy involved an absolute (buy and sell) orderflow of $100 million. 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.

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. One explanation for why the response to the bullet is between 33 and 119% greater (46 and 135% when liquidity is low) and for why the shape of the responses is quite different is that the barbell effectively splits the information content of the bullet trade into two independent transactions involving close substitutes. This split-up makes it considerably more difficult to decipher the information content of the transactions. Unless the counterparties know a priori that the two transactions are to be combined into the equivalent of a 5-year bullet, each transaction contains only a fraction of the information contained in the bullet. Furthermore, the two pieces do not add up to the information content of the bullet because of the exceptional sensitivity of the yield curve to transactions in the 2 to 5-year maturity range. From a practical perspective, this result illustrates the potential importance of splitting up large trades into smaller transactions in close substitutes, as a way of reducing price impact and thereby lowering transaction costs.

The term spread, which involves buying the 10-year bond and selling the 2-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 10-year bond is roughly four times that of the 2-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 2-year yield will rise (its price will drop) relative to the 10-year yield, the yield increase in response to the orderflow is 71% greater at the 2-year maturity than at the 10-year maturity. The results for the butterfly spread are equally intuitive. The butterfly spread involves selling the 5-year note and buying the 2-year note and 10-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 4, 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 6 to 64%, compared to 78 to 150% 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 $2 billion, 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% 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 an 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% 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 argue that this finding is consistent with market participants paying more attention to orderflow when the true valuations are uncertain. Finally, we illustrate the multidimensional aspect and practical relevance of our results in the context of common fixed income trading strategies.

We argue that our results are important for academics and practitioners alike. For academics, we raised three important issues that need to be considered when modeling U.S. Treasury securities. First, price discovery does occur in the Treasury market. Second, the price discovery process is focused within the on-the-run segment of the market, and, third, low liquidity magnifies the price discovery process. Given these results, theoretical term structure models may benefit from a better understanding of the heterogeneity of information across market participants and of the process through which this information is aggregated into market prices. For example, our result on the role of liquidity in the price discovery process suggests a link between the volatility of bond prices and the perceived disagreement about the bond price across market participants. A better understanding of how this disagreement evolves through time might help in the modeling of the bond price volatility dynamics.

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