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Macro News, Risk-Free Rates, and the Intermediary: Customer Orders for Thirty-Year Treasury Futures

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Abstract

Customer order flow correlates with permanent price changes in equity and non-equity markets. We examine macro news events in the thirty-year Treasury futures market to identify causality from customer flow to risk-free rates. We remove the positive feedback trading effect and establish that, in the fifteen minutes subsequent to the news, intermediaries rely on customer orders to determine a substantial part of the announcement's effect on risk-free rates—about one-third relative to the instantaneous effect. Intermediaries appear to benefit from privately observing informed customers, since their own-account trade profitability correlates with access to customer flow, controlling for volatility, competition, and the macro "surprise."

Key words: discount rate, macroeconomic announcements, customer order flow, intermediary, Treasury futures, informativeness

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Signed customer order flow correlates with permanent price changes.[1] In the equity market, a common explanation is that investors initiate trades based on private information on a stock's future dividends. There is, however, growing evidence that, beyond such idiosyncratic effect, order flow correlates with changes in the state of the economy.[2] Canonical models in microstructure[3] interpret such correlation as causality from order flow to prices, but a popular alternative hypothesis is reverse causality through feedback trading.

This paper aims to establish causality from customer flow to riskfree rates through an analysis of macro news in the 30Y treasury futures market. The key to identification is that we observe the news, its instantaneous effect on the riskfree rate, and the, indeed, positively correlated subsequent customer flow.[4] We document that, after removing the effects of feedback trading, the 5-minute change in the 30Y riskfree rate is significantly more sensitive to customer flow in the 15 minutes after the announcement. We decompose the (explained) 15-minute rate change variance and find that 76.0% is immediate and 24.0% is due to the (orthogonalized) customer flow.

We add to a growing body of empirical evidence on order flow in treasury markets. Brandt and Kavajecz (2004) find that order flow is a significant explanatory variable in daily treasury return regressions. As for macro news, early papers report an instantaneous effect, but also increased volatility in the minutes after the announcement.[5] And, consistent with our findings, Green (2004) documents increased sensitivity of treasury returns to order flow in the first 15 minutes after the announcement. Pasquariello and Vega (2007) find that the correlation increases with preannouncement dispersion of analyst forecasts. These papers are based on GovPX data, which contains the *interdealer* order flow of the interdealer brokers.

Our key contribution is to establish directly the increased sensitivity of riskfree rates to customer order flow. Such effect is difficult to identify indirectly from the interdealer flow examined by Green (2004). Although this interdealer flow reflects customer flow[6], its

[1]Customer buys (sells) get a positive (negative) sign.

[2]For equity markets, for example, Hasbrouck and Seppi (2001) identify a common factor in order flow that significantly correlates with daily market returns. Edelen and Warner (2001) find correlated mutual fund flow to be part of this factor. Saar (2007) proposes a model where order flow is informative on unknown preferences and endowments of investors. For the FX market, Evans and Lyons (2002) find that order flow explains more than 50% of daily DM/US$ returns. Moreover, Evans and Lyons (2007) find that (unobserved) monthly order flow predicts macro news that will be released in the oncoming months.

[3]E.g., Glosten and Milgrom (1985), Kyle (1985), and Stoll (1978).

[4]We decompose subsequent order flow variance and attribute 6.7% of the flow's explanatory power to positive feedback trading, i.e. net buying (selling) after a positive (negative) instantaneous price adjustment (see section 2).

[5]See, e.g., Ederington and Lee (1993) and Fleming and Remolona (1999).

[6]Dealers typically accommodate a customer order completely and then actively unload their inventory in the interdealer market. For example, a customer sell order therefore creates a series of sell orders in the

effect is not necessarily due to customer flow for two reasons. First, the intermediary might initiate trades based on a private signal orthogonal to customer flow.[7] For example, Anand and Subrahmanyam (2007) find that for the Toronto stock exchange the most informative trades are initiated by intermediaries unrelated to how much access they have to customer flow. Second, the intermediary could affect sensitivity *endogenously* through own-account trades on privately observing the composition of customer order flow. That is, she trades along with informed customers and opposite to uninformed customers. The aggregate (i.e. customer plus own-account) order she passes on to other market makers therefore amplifies the information part and reduces the noise part of the customer order. Zero-profit market makers rationally charge higher price concessions to protect themselves against such flow-based speculation.[8]

We analyze 42.5 million trades in the highly liquid 30Y treasury futures market in 1994 through 1997 for the following reasons. First, it allows us to discriminate customer trades from the intermediary's own-account trades. Second, we do not need an algorithm to sign trades, as the data identifies buyer and seller initiated customer trades. Third, it has a sizable cross-section of 3,382 intermediaries. Fourth, it is comprehensive, as 30Y treasury futures capture 95% of the trading volume in the spot and futures markets for this maturity.[9] Fifth, the 30Y maturity is likely to make this treasury bond very sensitive to changes in riskfree rates.

We further analyze postannouncement trading to establish that the increased sensitivity of riskfree rate changes to customer flow reflects information. We realize that in inactive markets any regression of price change on signed flow might pick up a transitory price effect to compensate for the cost of market-making. For example, the increased sensitivity might reflect that risk-averse dealers require higher compensation for carrying inventory through time on increased postannouncement volatility. We consider this noninformation explanation unlikely for our five-minute regressions in what is a very active market. That is,

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aggregate interdealer market. See Lyons (2001, Ch. 4.4) for a discussion of such "hot potato trading."

[7]Green (2004), e.g., offers as explanation for his findings that market participants vary in their ability to interpret the news, with reference to Kim and Verrecchia (1994, 1997).

[8]The idea that intermediaries benefit from discriminating informed from uninformed flow is well-established in the literature. Market markers cream-skim uninformed flow (see, e.g., Beneviste, Marcus, and Wilhelm (1992), Easley, Kiefer, and O'Hara (1996) and Chung, Chuwonganant, and McCormick (2004)). Brokers trade along informed flow (Fishman and Longstaff (1992)) or against uninformed flow (Roell (1990), Madrigal (1996)). Appendix A illustrates the idea in a Kyle (1985) setup and includes a rational response of the informed customer who reduces her order size in anticipation of the intermediary's speculation.

[9]This calculation is from Fleming and Sarkar (1999) who use 1993 spot market data for "on-the-run" securities (i.e. the most recently issued security in a maturity). The authors use GovPX data and adjust with GovPX coverage ratios to estimate total spot market volume (see also Fleming (2003)).

for an average announcement day five-minute interval, 172.9 intermediaries generate 595.9 transactions. Moreover, if we regress interest rate changes on the subset of customer orders that trades through intermediaries who do not trade for own-account that day, we find *unchanged* sensitivity. This is not an order size effect, as customer orders in this subset are larger than the average customer order. Therefore, we interpret the increased sensitivity result as consistent with flow-based speculation of intermediaries who endogenously choose to piggy-back on orders that they privately observe to originate from informed customers.

We exploit the cross-section of intermediaries and relate own-account profitability to customer flow access to provide direct evidence of flow-based speculation. We find two key results. First, we report that own-account trade profitability is higher for intermediaries who walk customer orders to the floor ("duals") relative to those who do not ("locals"), which controls for the cost of market-making.[10] Second, we exploit the cross-section of duals to show that their own-account profitability increases with access to customer flow, where we control for volatility, competition, and the macro "surprise." Intermediaries therefore appear to trade profitably on the information in customer flow, which feeds our earlier concern that (part of) the increased sensitivity of riskfree rate change to (aggregate) interdealer flow might be endogenously generated.

We entertain the alternative explanation that intermediaries with superior trading skill are likely to attract more customers (see, e.g., Grossman (1989)), which makes the correlation between own-account profitability and access to customer flow entirely spurious. To control for skill, we compare an intermediary's own-account profitability on announcement days where she has access to customer flow relative to announcement days where she does not and find significantly increased profitability on days where she has access to customer flow. Furthermore, we find that on the announcement days that she does not trade for customers, her own-account profitability is not significantly different from own-account profitability of locals. These results rule out that exceptional trading skill drives a dual trader's rents.[11]

We analyze customer profits to identify who pays the dual's rents on flow-based speculation. If fully competitive market makers cannot infer which order flow is informed, they rationally charge all flow an increased price concession and the dual's rents are, therefore, effectively paid for by all customers. If, on the other hand, they get a signal on which intermediary is likely to have the informed flow (and trades for own-account), they charge

[10]We find evidence consistent with an increased cost of market-making due to higher postannouncement volatility, as (gross) own-account profitability is higher (and bid-ask spreads are higher) on announcement days relative to nonannouncement days.

[11]We interpret trading skill broadly to include an ability to quickly process and interpret macro news as in Kim and Verrecchia (1994, 1997).

only her an increased price concession, and, as a result, only her customers pay the dual's rent. We find evidence for the latter explanation as dual-intermediated customer profits are lower than nondual-intermediated customer profits.

Finally, we contribute to the dual-trading literature. Chakravarty and Li (2003) study eight CME futures contracts and find that dual traders supply liquidity and actively manage inventory. Manaster and Mann (1996) corroborate these findings in their CME futures study, but, much to their surprise, also report a positive correlation between signed inventory and the intermediary reservation price. They conclude that intermediaries are not "passive order-fillers,... but active profit-seeking individuals with heterogeneous levels of information and/or trading skill." We establish that one channel is access to informative customer flow. Most related to our study is Fishman and Longstaff (1992) who emphasize that the decision to trade for own-account is endogenous, i.e. the intermediary does so if she has private knowledge on the composition of her customer order flow. Contrary to our results, they find for 15 random days soybean's futures trading that dual-intermediated customer profits are significantly *higher* than nondual-intermediated customer profits. We interpret their result as evidence that market makers do not get any signal as to which intermediary carries the informed flow.

The remainder of the paper is organized as follows. Section 1 discusses the institutional background, the data, and provides summary statistics. Section 2 studies customer order flow informativeness on announcement days (relative to nonannouncement days). Section 3 calculates the intermediary's own-account trading profit and relates it to access to customer flow. Section 4 analyzes who effectively pays the intermediary's rents. Section 5 concludes.

1 Background, data, and summary statistics

1.1 Background

We analyze four years (1994-1997) of trading in 30Y treasury futures at the Chicago Board of Trade (CBOT). At the time, this contract is one of the most liquid securities with roughly 50 trades per minute.[12] Almost all trading is floor trading from 8.20 a.m. to 3.00 p.m. Eastern

[12]See Table 2. Note that this table necessarily double-counts, as we also report trade activity by trader type. We double-count throughout the paper in order to be consistent.

Time (ET), although after-hours electronic trading volume had been growing. Trading occurs in a pit by means of the so-called open outcry method. Floor traders negotiate prices by shouting out orders to other floor traders, indicating quantity and trade direction through hand signals. Other floor traders bid on the orders, also using hand signals. Once filled, an order is recorded separately by both parties to a trade. At the end of the day, the clearinghouse settles trades and ensures that there is no discrepancy in the matched trade information.

After a criminal inquiry in 1989, the Commodity Futures Trading Commission (CFTC)—the main regulatory body of futures exchanges—continues to allow dual trading, but tightens surveillance. The FBI sting operation at the CBOT and the Chicago Mercantile Exchange (CME) finds that brokers (including dual traders) are cheating customers and leads to dozens of arrests. In 1992, Congress mandates that futures markets keep audit trails. The CFTC pressures both CBOT and CME to supply the information with the threat of a dual trading ban, in case the exchanges fail to comply.[13] Today, dual trading continues to be allowed in most futures markets. The exceptions are some CME futures contracts, mostly those with a history of high volume.

1.2 Data

Futures data. We benefit from the CFTC audit trail data to discriminate customer trades and own-account trades in the 30Y treasury futures market. Each transaction record contains: Contract traded (i.e. the expiration month); time[14]; buy or sell indicator; number of contracts traded; price; identification number for the floor trader who executes the trade; and a customer type indicator (CTI code). These CTI codes are defined in CFTC rule 1.35(e) as: CTI1 is a trade for own account; CTI2 is a trade for clearing member's house account; CTI3 is a trade for another member present at the exchange floor, or an account controlled by such other member; CTI4 is a trade for (off-exchange) customers. Consistent with earlier studies[15] we restrict attention to CTI1 and CTI4 trades as they represent most of the trading volume.

[13] See, e.g., "CFTC demands tighter controls," *Financial Times*, 8/13/96.

[14] Traders report time in 15-minute brackets and an exchange algorithm, known as computerized trade reconstruction (CTR), times the trade to the nearest second. Although noisy, we believe the CTR time is fairly accurate due to Congress and CFTC pressure to provide high-quality data for surveillance. Others have used CTR time for analysis, e.g. Fishman and Longstaff (1992) and Manaster and Mann (1996).

[15] E.g., Fishman and Longstaff (1992), Manaster and Mann (1996), and Chakravarty and Li (2003).

We focus on the nearby futures contract and apply a number of filters to prepare the data for analysis. We choose to analyze the nearby contract, as it is a very close substitute for the underlying spot instrument. Consequently, we feel that our results generalize to spot rates (see also Ederington and Lee (1993, p.1164)). We apply the following filters. We eliminate spread trades (e.g., butterfly spread trades). We remove trades that occur at unusually low prices (primarily in May 1997). We remove trades that show an unusual transaction return of more than 0.25% followed by a transaction return in the opposite direction of more than 0.25%. We expect these trades to suffer from a serious timing error. These filters eliminate 1.48% of all CTI1 and CTI4 transactions. The final sample includes 42.5 million observations.

Macro announcements We follow Green (2004) and use the International Money Market Services (MMS) data on expectations and realizations of the most relevant 8:30 U.S. macro announcements. We are careful to remove days with macro announcements scheduled at a time later in the day (primarily 10:00) to create benchmark nonannouncement days that are not contaminated by macro news trading.[16] We further remove (i) days when either the realized value or the expectation is missing, (ii) days when the Fed announces earlier or later relative to schedule, (iii) days with unexpected Fed announcements, (iv) days where the market is partially or completely closed.[17]

[insert Table 1]

Table 1 lists the 15 macro announcements included in the sample and reports their frequencies. In total, the sample contains 377 announcement days and 350 nonannouncement days. In addition to an analysis of all announcement days, we also analyze the subgroup of most influential announcements—nonfarm payroll employment, PPI, and CPI—but also "nonfarm payroll" as a separate group as it is the single most important announcement (see also, e.g., Green (2004, Table III)).

We define announcement surprises as the difference between realizations and expectations. More specifically, since measurement units vary across macro variables, we standardize the surprises by dividing each of them by their sample standard deviation. The surprise S_{kt} of type k on day t is therefore

$$S_{kt} = \frac{R_{kt} - M_{kt}}{\sigma_k} \tag{1}$$

[16] This also removes days with an 8:30 and a 10:00 announcement. The remaining announcement days are therefore 8:30-only announcement days.

[17] These days are 4/1/94, 4/5/94, 9/14/94, 8/26/96, 2/26/97, and 2/27/97.

where R_{kt} is the announced value, M_{kt} is its MMS median forecast that proxies for the market expectation, and σ_k is the sample standard deviation of $(R_{kt} - M_{kt})$. Eqn. (1) facilitates meaningful comparisons of how the 30Y riskfree rate responds to the different types of macro news. Operationally, we estimate these responses by regressing 30Y treasury futures price changes on the surprise S_{kt}. We note that since σ_k is constant for any indicator k, the standardization does not affect the statistical significance of the response estimates nor the fit of the regressions.

1.3 Summary statistics

[insert Figure 1]

Figure 1 plots transaction prices and volume on a random macro announcement day. It illustrates some trade characteristics that turn out to be true more generally. First, the 8:30 announcement leads to an instantaneous price change of almost 1%. Second, customer order flow increases by over 400% in the subsequent minutes, but levels off quickly. Third, during this time price changes, relative to preannouncement changes, are substantially higher and their direction appears to correlate with signed customer flow. These findings are consistent with earlier papers (see, e.g., Fleming and Remolona (1999) and Green (2004)).

[insert Figure 2]

Intraday patterns. Figure 2 presents the intraday patterns of volatility, the bid-ask spread, and volume. We use all 377 announcement days and 350 nonannoucement days to calculate the value for each 15-minute interval and we estimate the patterns through regressions. We use GMM for all regressions in the paper and we use robust Newey-West standard errors (where we allow for autocorrelation up to three lags). We plot our estimates and we add a closed (open) circle when the difference between announcement and nonannouncement days is significant at the 1% (5%) level.

Panel (A) shows that volatility is significantly higher in the first half of the announcement day with a clear peak in the first 15 minutes after the announcement. To avoid a bias due to the bid-ask bounce, we define volatility as the standard deviation of customer buy transaction prices[18] (see also Manaster and Mann (1996)). We find a significant spike

[18]Operationally, to minimize missing values, we calculate two standard deviations, one based on customer buys, the other on customer sells. We take the maximum if both are available.

in volatility of roughly 300% in the 15 minutes after the announcement. For the rest of the day, volatility levels remain increased relative to nonannouncement days, but the increase is substantially lower as it never exceeds 25%. The increase is statistically significant only in the early half of the day.

Panels (B) and (C) show a significant volume increase throughout the trading day, but, interestingly, we only find a significantly increased bid-ask spread in the first 15 minutes after the announcement. We report aggregate volume (i.e. customer plus own-account volume) and find its increase to be similar in magnitude to the volatility increase. We estimate the bid-ask spread as the difference between the average (volume-weighted) customer buy price and the average customer sell price (see also Manaster and Mann (1996)). We only find a significant increase at the 1% level in the first 15 minutes after the announcement. Economically, the increase is substantial as it exceeds 120%.

All in all, these patterns are consistent with Green (2004) who documents increased informed trading only for the first 15 minutes after the announcement. Our volatility and bid-ask spread patterns are consistent. The increased volume in the remainder of the day might reflect inventory-sharing trades among market makers who are pushed into suboptimal positions in the first 15 minutes.

Customer vs. own-account trades. As it is our objective to further understand these trading patterns, we exploit our sample's feature that it discriminates customer trades and own-account trades. We follow the literature (see, e.g., Fishman and Longstaff (1992)) and disaggregate volume for each day according to (i) whether the intermediary trades for customers and own-account that day[19] and (ii) whether the trade is a customer trade or an own-account trade. We label the order flow accordingly, i.e. we get four categories:

1. Customer trades through brokers, i.e. customer trades through an intermediary who does not trade for own account

2. Own-account trades by locals, i.e. own-account trades of an intermediary who does not trade for customers

3. Customer trades through duals, i.e. customer trades through an intermediary who also trades for own account

[19]We use a 2% error margin for classification (i.e., no own-account trades means less than 2% of the intermediary's trades are for own-account) as CFTC and exchange staff acknowledge the presence of error trades and consider the 2% filter reasonable (see Chang, Locke, and Mann (1994)).

4. Own-account trades by duals, i.e. own-account trades of an intermediary who also trades for customers

We emphasize that an intermediary's label as broker, local, or dual is based on her activity on a particular day and, throughout the sample, an intermediary can therefore have broker days, local days, and dual days.

[insert Table 2]

Table 2 presents trade statistics for announcement as well as nonannouncement days. Panel A testifies to the high activity in the 30Y treasury futures market. On nonannouncement days, we find that, on average, in a five-minute interval 146.0 traders are active who generate 458.2 transactions. On announcement days, the number of active traders increases by 18% and the number of transactions by 30%.

Panel B disaggregates activity according to intermediary type and finds, for nonannouncement days, that the majority of active intermediaries acts as local (65%)[20], followed by dual (28%), and broker (7%). Clearly, dual activity continues to be substantial in the aftermath of the 1992 Congress mandate (see section 1.1), in particular with regard to customer trades. For the average five-minute interval, 34.5 duals carry out an aggregate 90.9 transactions for their customers vis-à-vis 7.9 brokers who carry out 21.4 customer transactions.[21] Trade size is higher for brokers, but even in terms of volume duals carry out most customer orders. Furthermore, bid-ask spread is higher for customer trades through duals vis-à-vis brokers, which is a first indication that their order flow includes the informed customer orders.

For announcement days, activity is higher across all trader types, trades are larger, and bid-ask spreads are higher. These changes appear to be proportional across trader types, so that on a relative basis the nonannouncement day characterization of trading remains true for announcement days. The same goes for the first 15 minutes after the announcement with the exception that the proportional increase in customer trades is larger than the increase in own-account trades.[22]

[20] 100%*81.4/(81.4+35.4+7.9).

[21] Note that we find a slight difference between the number of duals active based on own-account counting (35.4 per five-minute interval) or for-customer counting (34.5). This difference is due to the counting procedure, as, apparently, a dual's own-account trading is more spread out in the day, while her costumer flow concentrates in some intervals.

[22] These results are not included for brevity, but are available upon request.

2 Customer order informativeness

In this section, we pursue our main objective, which is to establish the increased informativeness of customer flow after a macro announcement. We consider this an important result, as it shows that intermediaries need off-exchange customer response to fully appreciate the effect of the macro announcement on the 30Y riskfree rate. Saar (2007) interprets such response as intermediaries who learn from imperfectly known endowments and preferences. Previous studies, most notably Green (2004), document empirical support, but they rely on interdealer flow. As mentioned in the introduction, this flow is "contaminated" by potential superiorly informed intermediaries or, endogenously, by dual trading (see Appendix A).

2.1 Five-minute price change regressions on customer flow

We assess customer flow informativeness through a regression of five-minute price changes on aggregate signed customer flow. We prefer time-interval return regressions (as in Brandt and Kavajecz (2004) and Pasquariello and Vega (2007)) to trade return regressions (as in Green (2004)), as the aggregation alleviates any effect time-stamp errors might have. Consistent with previous studies, we add the macro surprise to the regression and estimate:

$$p_{t,h} - p_{t,h-1} = d_a(\alpha_a + \beta_a \omega_{t,h}) + d_n(\alpha_n + \beta_n \omega_{t,h}) + \sum_k \gamma_k I_{k,t} S_{k,t} + \varepsilon_{t,h} \tag{2}$$

where $p_{t,h}$ is 100 times the log price (to get % returns) at day t and five-minute interval h, d_a (d_n) is a dummy that is one on an announcement (nonannouncemement) day, zero otherwise, $\omega_{t,h}$ is the aggregate signed customer volume, $S_{k,t}$ is the announcement surprise (see equation (1)), $I_{k,t}$ is a dummy that is one for the time interval immediately after the announcement, zero otherwise, and $\varepsilon_{t,k}$ is the error term. The regression implicitly controls for feedback trading through inclusion of the macro surprise, i.e. any effect of $\omega_{k,t}$ is identified off of the orthogonalized component relative to the other explanatory variables.[23] We emphasize that this is a contribution of our approach, as Green (2004, p.1210) only includes the surprise in the first transaction return after the announcement and therefore orthogonalizes only the first postannouncement transaction.

[23]This relies on one of the statistical properties of linear regression, which is that any multivariate regression coefficient can be obtained through univariate regression of the orthogonalized dependent variable on the orthogonalized explanatory variable, where the orthogonalization is with respect to the other regressors.

[insert Figure 3]

Figure 3 depicts the intraday pattern of customer flow informativeness on announcement as well as nonannouncemement days. We estimate equation (2) separately for all 15-minute intervals in the trading day and test whether the customer flow's informativeness (β) is significantly different on announcement days. We find it to be significantly higher in the 15 minutes subsequent to the announcement and generally insignificant for the remainder of the day. Economically, informativeness roughly doubles and the intraday pattern is therefore comparable—in shape and magnitude—to the bid-ask spread pattern.

[insert Table 3]

Table 3 presents the regression estimates for the 15 minutes after the announcement (Panel A) and includes the macro surprise coefficients (Panel B). We find that 9 out of the 15 announcement surprises significantly affects subsequent returns, where, generally, procyclical announcements (e.g., nonfarm payroll employment) negatively affect returns and countercyclical announcements (e.g., initial unemployment claims) positively affect returns. Among these announcements, we find that nonfarm payroll employment, producer price index (PPI), and consumer price index (CPI) have the largest economic impact. We therefore repeat all regressions with only these three announcement days and with only nonfarm payroll announcement days to, hopefully, find that any effect we find increases with the importance of the news. Panel A shows that this is indeed the case for the customer flow informativeness differential across announcement and nonannouncement days.

We decompose the explained price change variance and find that 24.0% is due to customer order flow where we control for feedback trading. The R-squared reported in Panel A, shows that the announcement day regression explains 36.6% of price change variance. We use a Cholesky decomposition on the explained part to judge how much is due to the immediate response to the announcement surprise and how much is due to subsequent customer flow. In the ordering, we choose to put the announcement surprise first so that effectively the contribution of customer flow is *net* of the component correlated with the announcement surprise. That is, mathematically, the effect it assigns to customer flow is based on customer flow orthogonalized relative to the surprise. The decomposition assigns 76.0% to the immediate response and 24.0% to (orthogonalized) customer flow. In the procedure, we find that 6.7% of the explanatory power of customer flow is effectively due to feedback trading as it is the size of the part that correlates with the announcement surprise.[24]

[24]We decompose the variation of $X'\beta$ where X is the matrix of explanatory variables and β is vector of coefficient estimates. The customer flow is the last element in the X. Cholesky decomposes the customer flow

2.2 An alternative interpretation of the regression coefficient

So far, we interpret our regression coefficient as trade informativeness. In inactive markets, part of the price change correlated with order flow is transitory in nature in order to compensate a liquidity supplier for the cost of market-making. We consider such effect unlikely for our five-minute regressions in what is a very active market; we find 172.9 intermediaries active who collectively generate 595.9 transactions in the average five-minute interval on announcement days (see Table 2).

[insert Table 4]

We rerun the regressions with decomposed customer flow to provide further evidence of informativeness. We decompose customer flow according to whether it reaches the floor through brokers (who do not trade for own-account that day) or through duals. The results in Table 4 show that yield changes are only significantly more sensitive to dual-intermediated customer flow on announcement days. The unchanged sensitivity to broker-intermediated customer flow is not a straightforward result of order size, as, if anything, brokers intermediate larger customer orders than duals do (see Table 2). Thus, this differential in sensitivity across dual- and broker-intermediated flow rules out a noninformation explanation based on increased price concession due to market-making costs, as this would affect all customer flow equally. Rather, we believe that the intermediary's decision to trade for own account is endogenous and depends on whether she traces informed customers in her customer flow in the aftermath of the announcement. We note that this result is consistent with the higher bid-ask spread reported for dual-intermediated customer trades relative to broker-intermediated customer trades (see section 1.3).

3 Intermediary's own-account trading

With the result of increased customer flow informativeness after an information event, we analyze whether intermediaries benefit from direct access to customer flow through own-account trading. As mentioned in the introduction, screening out the customer flow and

(explanatory) variation into a part that is projected onto the macro surprises ("feedback part", 6.7%) and an orthogonalized part (93.3%). In the procedure we subtract off of the orthogonalized part the explained variation on nonannouncement days to single out the effect due to the *increased* informativeness.

discriminating informed from uninformed customers, the intermediary's rational strategy is to trade along with informed customers and opposite to uninformed orders (see Appendix A).

3.1 Is direct access to customer flow profitable?

We analyze own-account trading profitability for intermediaries with access to customer flow (duals) and intermediaries without such access (locals) in the 15 minutes after the announcement. We follow Fishman and Longstaff (1992) and define profitability as:

$$\pi_{kt} = \left(\sum_{j=1}^{N_{kt}^s} q_{jkt}^s P_{jkt}^s - \sum_{j=1}^{N_{kt}^b} q_{jkt}^b P_{jkt}^b + (\sum_{j=1}^{N_{kt}^b} q_{jkt}^b - \sum_{j=1}^{N_{kt}^s} q_{jkt}^s) REFP_t \right) / \max(\sum_{j=1}^{N_{kt}^b} q_{jkt}^b, \sum_{j=1}^{N_{kt}^s} q_{jkt}^s) \tag{3}$$

where π_{kt} is the profit per round-trip contract[25] for intermediary k on day t, N_{kt}^b (N_{kt}^s) is the total number of buys (sells), q_{jkt}^b (q_{jkt}^s) is the quantity of the jth transaction in terms of number of contracts, P_{jkt}^b (P_{jkt}^s) is the associated price, and $REFP_t$ is the reference price in day t. The profit calculation assumes that the intermediary starts with zero inventory and liquidates his end-of-period position at a reference price $REFP_t$. We present results where we set the reference price equal to the last transaction price in the measurement interval. For robustness, we also analyze profits based on the end-of-day settlement price as reference price, which gives qualitatively similar results.[26] We note that, by construction, this profit is net of adverse-selection cost (as it aggregates across multiple subsequent transactions and therefore includes losses due to adverse selection), but gross of market-making cost (e.g., inventory cost, order-procession cost).

[insert Table 5]

Table 5 reports round-trip profitability per contract for duals and locals on announcement and nonannouncement days. We find very large standard deviations due to some extreme positive and negative observations. We therefore prefer a nonparametric test on median differences to the standard test on mean differences (see also Fishman and Longstaff (1992)). A * (**) indicates a significant difference between announcement and nonannouncement days at the 5% (1%) level, whereas x (xx) indicates a significant difference between dual profitability and local profitability. We emphasize two important results.

[25] We use a per-contract profit measure to control for trade activity, as locals are more active than duals.
[26] Available from the authors upon request.

First, we find that a local's profitability on own-account trading is higher on announcement days and increases with the importance of the announcement. We find that locals make a median $0.0 per contract traded round-trip on nonannouncement days. It is significantly higher on announcement days, $7.8, which amounts to an approximate[27] $1,063 per local for the full 15 minutes. It further increases with the importance of the announcement to $14.8 per contract on nonfarm, PPI, and CPI days to $23.7 on the nonfarm days. We interpret this as evidence of increased profits to compensate for the higher cost of carrying inventory through very volatile times.

Second, we find that duals appear to benefit from direct access to customer flow as they trade more profitably for own-account than locals do and, more importantly, this differential is higher on announcement days. We find that duals make a median $2.2 per contract on nonannouncement days, which is significantly higher than the $0.0 locals make. The result indicates that customer order flow is informative even on nonannouncement days. The important result, however, is that this differential is significantly higher on announcement days. Round-trip profit per contract is $6.1 ($13.9-$7.8) higher for duals on announcement days, $8.0 higher on nonfarm, PPI, and CPI days, and $7.6 higher on nonfarm days.

3.2 The alternative explanation: superior trading skills

Fishman and Longstaff (1992) entertain the alternative explanation that some traders have superior trading skill—trade more profitably for own-account—and customers choose to trade through these intermediaries to benefit from their skill. Thus, the correlation we document between trading for customers and own-account profitability might be entirely spurious. To control for skill, Fishman and Longstaff (1992, Table 4) analyze trading profit of "nonpure" duals, i.e. intermediaries who some days trade for own-account only (local days) and other days trade both for own-account and for customers (dual days). We use the same approach in our sample.

[insert Table 6]

Panel A of Table 6 reports the profit differential of nonpure duals on the days they have access to customer flow relative to the days that they do not (i.e. own-account prof-

[27] Based on 264.0 ("single-trip") transactions of 11.3 contracts by 81.4 locals per five minutes on nonannouncement days, a volume increase of 300% in the 15 minutes subsequent to an announcement, a 21% increase active locals and a negligible increase in trade size on announcement days, i.e. $\$1.063 \approx \$7.8*264*.5*11.3*3*3/(81.4*1.21)$ (see Table 2 and Figure 2).

itability on dual days minus own-account profitability on local days). We find that, on their dual days, they earn a significantly higher profit than on their local days—the median differential is \$5.6 per round-trip contract. We then separate announcement and nonannouncement days and do the same analysis. Interestingly, we find a significantly increased profit for announcement days only. For nonannouncement days, we find no statistical difference, consistent with Fishman and Longstaff (1992). We conclude that, after control for trading skill, we continue to find support for the premise that intermediaries need the off-exchange customer flow to fully appreciate the effect of macro news and benefit from discriminating the informed traders in their customer flow.

Panel B compares a nonpure dual's local-day profit to a (pure) local's profit and finds no evidence of superior trading skill. For nonannouncement days, we find a profitability of \$0.0 and \$0.1 on local days of nonpure duals and locals, respectively, which are not significantly different. For announcement days, profitability is \$7.8 and \$7.8, respectively, which, again, are not significantly different. The increased profits for announcement days could very well reflect more costly inventory-keeping. The insignificant difference between the local-day profit of nonpure duals and locals indicates that duals do not show superior skill in interpreting the macro news. Hence, this is further evidence that access to customer flow is the main cause for a dual's increased profitability on announcement days.

3.3 Do profits increase with the level of customer flow access?

We exploit the cross-section of duals to further establish a relationship between own-account profitability and access to customer order flow. We regress profit per contract of dual trader l in the 15 minutes of postannouncement trading, π_{lt}, on a measure of access to customer flow and various control variables:

$$\pi_{lt} = \alpha + \beta_1 CUST_{lt} + \beta_2 VOLA_t + \beta_3 COMP_t + \sum_k \gamma_k |S_{kt}| + \varepsilon_{lt} \tag{4}$$

where $CUST_{lt}$ proxies for dual l's access to customer flow (e.g., number of customer trades executed) in the 15 minutes following the announcement on day t, $VOLA_t$ is the volatility measure (see section 1.3), $COMP_t$ is a competition proxy and is defined as the ratio of the number of active intermediaries who trade for customers (i.e., dual and brokers) and the number of customer trades, S_{kt} is the macro surprise of announcement type k, and ε_{lt} is the error term.[28] We control for a potential competition effect, as Wahal (1997), for example, finds that the number of dealers matters for the bid-ask spread in the NASDAQ market, which he interprets to be "consistent with the competitive model of dealers pricing." We relate a dual trader's profit to her access to customer flow and, therefore, build a competition proxy on how many rivals she has for each customer trade (i.e., duals and brokers). In addition to equation (4), we perform a regression where we replace all control variables by a day dummy to kill all the time effect and we therefore only get traction from the cross-section.[29] This makes it generally harder to find a significant estimate of β_1.[30]

[insert Table 7]

Table 7 shows that a dual's own-account profitability increases with access to customer flow ($\beta_1 > 0$), which is only significant when we use proxies based on customer trades rather than customer volume. We number the regression results based on the four proxies we use to measure access to customer flow: The number of trades, the sum of signed trades, volume, and the sum of signed volume. We use trades as well as volume to account for potential trade size effect and we use signed and unsigned to account for a potential imbalance effect. Per proxy, we perform three regressions: A univariate regression, a regression with controls, and a regression with day dummies. The univariate results show a positive coefficient for access to customer flow, but it is significant only for the trade-based proxies (i.e. the number of trades and the sum of signed trades). This significance is robust to addition of control variables or time dummies. And, consistent with our expectations, we find that profits increase with volatility (e.g., to reflect more costly inventory keeping) and decrease with the level of competition.

The finding that only the trade-based proxies explain profitability significantly (as opposed to the volume proxies) is not surprising in view of the flow-based speculation result that the intermediary benefits from discriminating informed from uninformed customer flow. That is, she has more scope to discriminate if the number of trades increases on unchanged volume, as she then interacts with more customers. Economically, the effect is substantial, as a one standard deviation change in the number of trades executed for customers earns the intermediary an additional \$2.2 per contract on her own-account trades, which is a 15% increase relative to her \$13.9 median profit on announcement days.[31]

[28] For ease of exposition, we use the indicator l to relabel duals every day.

[29] This is the only regression where we have to revert to OLS as the addition of time dummies makes the GMM procedure too demanding numerically.

[30] The model with controls is nested in the time dummy model, as the controls are effectively spanned by the time dummies, i.e. they are a linear combination of these dummies.

[31] See Table 2 and Table 7.

4 Who pays the dual's rents?

The previous section documents that intermediaries with direct access to customer flow benefit through own-account trading. We interpret this result as evidence of flow-based speculation, where the intermediary privately observes the identity of the submitting customer. In appendix A, we illustrate the mechanism in a simple extension of the Kyle (1985) model where the intermediary benefits from discriminating informed from uninformed customer flow. She trades in the same direction as her informed customer and opposite to her uninformed customer.

In the single intermediary world with a rational, zero-profit market maker, the intermediary's rents are paid for by her customers through an increased price concession the market maker charges to protect herself against flow-based speculation. In an multiple intermediaries setting, who pays the dual's rent critically depends on the extent that market makers can infer which intermediaries are likely to engage in flow-based speculation. The extremes are that (i) market makers get no signal or (ii) that they can fully discriminate the flow-based speculators. In the first case, they charge all intermediaries the same price concession and the dual's rents are effectively paid for by all customers. In the second case, the market maker only charges increased price concession to the flow-based speculators and, as a result, only their customers pay the rents.

4.1 Profitability of dual- and broker-intermediated customer orders

We analyze customer profits in the aftermath of the announcement to find whether dual-intermediated customers pay a disproportionate part of their intermediary's rents. We calculate customer profits based on equation (3) where we replace the intermediary's own-account trades (CTI1) by customer trades (CTI4).

[insert Table 8]

Table 8 shows that a dual's customer seems to pay a disproportionate part of her rents. We find that on announcement days the broker-intermediated customer trades earn a $0.0 median profit per round-trip contract, whereas dual-intermediated profit is significantly lower and amounts to \$-7.3 per contract.[32] This difference remains for the narrower sets of important announcements, but it is insignificant potentially as a result of low power due to the shrinking sample size. Fishman and Longstaff (1992), on the other hand, find significantly higher profit for dual-intermediated customer flow, which is the null based on a model where market maker cannot infer which intermediary has the informed customer orders. That is, she charges all the same price concession, which should make customer profits higher for dual-intermediated customer flow as it contains the positive profit of the informed customer order. The broker-intermediated customer flow does not contain such informed orders. We interpret our result as a sign that marker makers do get a signal on who has the informed customer flow and rationally charge them an additional price concession (to protect themselves against flow-based speculation).[33] This interpretation is consistent with our earlier result that the bid-ask spread is higher for dual-intermediated customer orders relative to broker-intermediated ones.

4.2 Why do customers trade through duals?

If customers that trade through duals pay disproportionately, why do they choose to trade through these intermediaries? In this section, we entertain several explanations. A key difference between the explanations is persistence. That is, do intermediaries persistently act as duals and brokers, so that market makers can infer their profile?

If not, customers do not really have a choice and, unconditionally, they do not pay disproportionately. Absent persistence, customers do not know ex ante whether their intermediary will get informed customer orders (and become dual) and they therefore do not really have a choice. It is in the interest of informed customers to hide their type as much as they can, which is consistent with switching intermediaries regularly.

If, on the other hand, there is persistence, the question is interesting: Why do customers stay with an intermediary who trades for own account? One explanation is that these intermediaries have superior trading skill. In section 3.2, we analyze trading skill and do not find supportive evidence. Another explanation is that they receive unobserved

[32] The negative sign is intuitive as it indicates that customers pay for demanding liquiditiy.

[33] We find indirect supportive evidence based on ranking dual traders according to the number of dual trader days. We find that customer profits of duals with more than median dual trader days are significantly lower than customer profits of those with less than median dual trader days. If we assume that duals with many dual trader days are easier to detect by the trading pit, then one could interpret this result as supportive evidence. For brevity, we omit the table, but it is available from the authors upon request.

benefits, such as reduced commissions or free access to analyst reports.

5 Conclusion

We exploit detailed data on 42.5 million transactions in the 1994-1997 30Y treasury futures market, which is a comprehensive dataset as it captures 95% of total volume (i.e. including the underlying). We are able to discriminate the off-exchange customer orders and find that they exhibit increased informativeness in the 15 minutes after an information event, i.e. an 8:30 macro announcement. This suggests that intermediaries rely on off-exchange order flow to fully appreciate how macro news affects the 30Y riskfree rate. Green (2004) documents the increased informativeness for interdealer order flow; we contribute and show that one channel is off-exchange customer "response" to the news. One interpretation is that intermediaries learn about imperfectly known preferences and endowments in the economy (see, e.g., Saar (2007)).

The data also enable us to analyze whether intermediaries who walk the customer orders to the floor, benefit from the informed flow through own-account trading. We find that in the 15 minutes after the announcement, they trade significantly more profitable for own account than other intermediaries without direct access to customer flow: For example, median profit per contract is 78% higher in the 15 minutes after the announcement. Additional analysis rules out the alternative explanation that these have superior trading skill. We interpret the evidence as flow-based speculation by intermediaries, i.e. contrary to those who do not have access to customer flow, they see the origination of the customer order and trade along with it for own-account if it is an informed order, but opposite to it if it is an uninformed order. Market markers rationally charge higher price concession and customers therefore pay the intermediary's rents. We analyze the cross-section of customer profitability and find that dual-intermediated customer flow appears to pay disproportionately.

We consider our evidence on flow-based speculation useful for regulators. Ultimately, customers pay the rents that intermediaries earn. This does not imply that flow-based speculation should be banned, as customers can choose their own intermediary (if any) and internalize the cost of flow-based speculation. We do, however, see a potential role for transparency regulation, so that a customer can evaluate her intermediary's performance. We realize that transparency is costly or might arise endogenously. We leave this issue for future research.

Finally, one might think that with the arrival of electronic limit order markets the issue of flow-based speculation disappears. We notice, however, that in these markets with the potential of direct access, intermediaries have all but disappeared. We interpret this as evidence that trading through intermediaries has certain benefits. Our study highlights one important cost, which is flow-based speculation.

Appendix A

In this appendix, we use the Kyle (1985) model to illustrate that price impact is increased in the presence of an intermediary who trades for her own account. The key engine for this result is that, contrary to the intermediary, the market maker does not observe the composition of customer flow. The intuition is that the rents earned by the intermediary are paid for by customers through an increased price impact (as the market maker earns zero rents).

Suppose v, the unknown payoff of the asset, is normally distributed with zero expectation and variance equal to σ_v^2. The customers consist of an informed investor who knows v and an uninformed investor who exogenously trades an amount u, which is normally distributed with zero expectation and variance σ_u^2.

Without an intermediary, Kyle (1985) finds the following unique linear equilibrium:

$$X(v) = \beta v, \quad \beta = \frac{1}{2\lambda} \quad \text{(linear strategy of informed investor)} \tag{5}$$

$$P(\omega) = E[v|\omega] = \lambda\omega, \quad \lambda = (\frac{1}{2})^{\frac{1}{2}}\frac{\sigma_v}{\sigma_u} \quad \text{(market maker earns zero rents)} \tag{6}$$

where $\omega = X(v) + u$ is the aggregate order flow the market maker receives.

We deviate from the standard setting and introduce an intermediary who observes the origination of the customer order and adds her own order y before submitting the aggregate order flow to the market maker. We restrict y to be a linear order:

$$y = \alpha v + \gamma u \tag{7}$$

The informed trader rationally anticipates the intermediary's action and internalizes her response when choosing β. We work backward and solve sequentially:

1. We condition on λ and β to maximize the intermediary's expected profit:

$$E[(P-v)y] = E[(\lambda\omega - v)y] = E[\lambda((\alpha+\beta)v + (1+\gamma)u) - v)(\alpha v + \gamma u)] \tag{8}$$

   which yields:

$$\alpha = \frac{1}{2}(\frac{1}{\lambda} - \beta), \quad \gamma = -\frac{1}{2} \tag{9}$$

   We find that (i) the intermediary trades less aggressively on the true value v if the informed customer submits a larger order (higher β) or if liquidity is lower (higher λ) and that (ii) she rationally takes the opposite side of the uninformed order ($\gamma < 0$).

2. We condition on λ and on the intermediary's action to maximize profits for the informed trader and find:

$$\beta = \frac{1}{2\lambda} \tag{10}$$

   The result is that the aggregate order loads more heavily on the signal ($\alpha+\beta = \frac{3}{4\lambda} > \frac{1}{2\lambda}$ (see equation (5)) as the informed trader now competes with the intermediary on her information.

3. Given the optimal strategy of the intermediary and the informed trader, we find λ by setting the risk-neutral market maker's expected profit equal to zero, i.e.

$$E[v|\omega] = \lambda\omega \Leftrightarrow \frac{cov(\omega, v)}{var(\omega)} = \lambda\omega \Leftrightarrow \lambda = (\frac{3}{4})^{\frac{1}{2}}\frac{\sigma_v}{\sigma_u} > (\frac{1}{2})^{\frac{1}{2}}\frac{\sigma_v}{\sigma_u} \quad \text{(see equation (6))} \tag{11}$$

   where $\omega = ((\alpha+\beta)v + (1+\gamma)u)$ is the aggregate order the market maker receives. Eqn. (11) shows that the price impact is increased in the presence of an intermediary and identifies two sources for the increased impact. First, the covariance in the numerator is increased due to more aggressive trading on the value v. We note, however, that the denominator is also increased to reflect the larger size of the order. Second, we find that the denominator is decreased due to less *net* "noise" trading as a result of the intermediary's strategy to trade opposite to the uninformed order.

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Table 1: Announcement and Nonannouncement Days

This table shows the number of announcement and nonannouncement days in our sample, and the frequency of each announcement. The data on macroeconomic announcements is from the International Money Market Services (MMS). The announcement days are days on which there is an 8:30 announcement and no other announcement in the morning (i.e., no 9:15 and 10:00 announcements). Nonannouncement days are days on which there are no announcements at all in the morning. There are three groups of announcement days: the first group contains all 8:30 announcements, the second group consists of the important announcement types (Nonfarm Payroll Employment, PPI, and CPI), and the third group contains only the Nonfarm Payroll Employment announcements. We exclude days when either the realized value or the expectation is missing, days on which the Fed made an earlier than usual or an unexpected announcement, the day on which the Durable Goods Orders figure was announced at 09:00 or 10:00, two days on which the market closed at 11:00 (4/1/94 and 4/5/96) and four days on which the market closed for a part of the day (9/14/94, 8/26/96, 2/26/97 and 2/27/97).

Panel A: Announcement vs. Nonannouncement Days					
	1994	1995	1996	1997	Total
All Trading Days	253	250	252	250	1,005
Nonannouncement Days	84	91	88	87	350
All Announcement Days	98	90	89	100	377
Nonfarm, PPI, and CPI	27	26	25	27	105
Nonfarm Payroll Employment	9	8	7	10	34
Panel B: Announcement Types and Frequencies					
Announcement Type	1994	1995	1996	1997	Total
GDP Advance	3	4	1	4	12
GDP Preliminary	3	1	1	2	7
GDP Final	3	0	5	2	10
Nonfarm Payroll Employment	9	8	7	10	34
Retail Sales	9	11	9	12	41
Personal Income	5	3	5	4	17
Personal Consumption Expenditure	5	3	5	4	17
Durable Goods Orders	11	11	8	7	37
Business Inventories	0	0	0	7	7
Net Exports	12	10	11	11	44
Producer Price Index	11	11	11	10	43
Consumer Price Index	7	7	7	7	28
Housing Starts	11	9	10	9	39
Index of Leading Indicators	5	2	6	6	19
Initial Unemployment Claims	40	37	36	43	156

Table 2: Trade Statistics by Trader Type

In Panel A, we show the average number of active traders, number of transactions and trade size per five minute interval for the 30Y treasury futures listed on the Chicago Board of Trade (CBOT) on both announcement and nonannouncement days. In Panel B, these variables, together with bid-ask spread (in $), are shown for different trader types. We define a floor trader to be a local (broker) on a day if the proportion of volume for her own account, as a ratio of total (own-account + customer) volume, is greater than 98% (smaller than 2%). A floor trader is a dual on a day if this proportion is greater than or equal to 2% but less than or equal to 98%. The sample period is from 1994 to 1997.

Panel A: Overall (five min avg)			
	Ann	Nonann	Ratio
#Traders Active	172.9	146.0	1.18
#Transactions	595.9	458.2	1.30
Trade size	12.4	11.6	1.07

Panel B: Breakdown according to Trader Type (five min avg)						
	Own Account (CTI 1)			For Customer (CTI 4)		
	Ann	Nonann	Ratio	Ann	Nonann	Ratio
#Traders Active	138.3	116.8	1.18	50.9	42.4	1.20
as a local	98.3	81.4	1.21			
as a dual	40.0	35.4	1.13	41.3	34.5	1.20
as a broker				9.6	7.9	1.21
#Transactions	450.3	345.9	1.30	145.7	112.3	1.30
through local	353.3	264.0	1.34			
through dual	96.9	81.8	1.18	117.4	90.9	1.29
through broker				28.2	21.4	1.32
Trade Size	10.9	10.2	1.07	17.5	16.1	1.09
through local	12.0	11.3	1.06			
through dual	6.9	6.5	1.07	16.8	15.2	1.11
through broker				20.6	19.6	1.05
Bid-Ask Spread[a] (in $)				6.4	5.6	1.14
through dual				6.7	5.9	1.13
through broker				4.3	3.4	1.26

[a] *We estimate the bid-ask spread as the difference between the average (volume-weighted) customer buy price and the average customer sell price (see also Manaster and Mann (1996)).*

Table 3: Regressions of 30Y Treasury Return on Customer Order Flow

This table reports the estimation results of the following regression:

$$p_{t,h} - p_{t,h-1} = d_a(\alpha_a + \beta_a \omega_{t,h}) + d_n(\alpha_n + \beta_n \omega_{t,h}) + \sum_k \gamma_k I_{k,t} S_{k,t} + \varepsilon_{t,h}$$

where $p_{t,h}$ is 100 times the log price of the 30Y treasury futures at day t and five minute interval h, d_a (d_n) is a dummy that is one on an announcement (nonannouncement) day, zero otherwise, $\omega_{t,h}$ is the aggregate signed customer volume divided by 1,000, $S_{k,t}$ is the announcement surprise, $I_{k,t}$ is a dummy that is one for the time interval immediately after the announcement, zero otherwise, and $\varepsilon_{t,k}$ is the error term. For estimation, we use the Feasible Efficient GMM procedure with a Newey-West estimator (using three lags) for standard errors. Panel A reports the estimates of the intercept and customer order flow coefficients estimated for 8:30-8:45 based on five minute intervals and tests for equality of customer order flow coefficients. Panel B presents the coefficients of the various macro surprises for the "all announcements" sample (the other samples show similar results). We report t-values below coefficient estimates.

Panel A: 30Y Treasury Return Regressions

			All Ann	Nonfarm, PPI, and CPI	Nonfarm Payroll Emp.
Customer Flow	Ann	β_a	0.0493**	0.0544**	0.0571**
			10.4	6.06	3.77
	Nonann	β_n	0.0256**	0.0256**	0.0256**
			9.67	9.67	9.67
Intercept	Ann	α_a	−0.0118**	−0.0364**	−0.0974**
			−2.75	−2.69	−3.26
	Nonann	α_n	0.0033*	0.0033*	0.0033*
			2.32	2.32	2.32
#Observations	Total		2,181	1,365	1,152
	Ann		1,131	315	102
	Nonann		1,050	1,050	1,050
R^2			0.366	0.354	0.369
p-value of H_0: $\beta_a = \beta_n$			0.0000**	0.0021**	0.0410*

/ indicates significance at the 5%/1% level.*

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Panel B: Announcement Surprise Coefficients		
Announcement type	Surprise Coefficient	t-value
GDP Advance	-0.085*	-2.13
GDP Preliminary	-0.203	-1.68
GDP Final	0.036	1.91
Nonfarm Payroll Emp.	-0.469**	-3.06
Retail Sales	-0.111**	-2.95
Personal Income	-0.006	-0.27
Pers. Consumption Exp.	0.007	0.30
Dur. Goods Orders	-0.105**	-3.97
Business Inventories	-0.098*	-2.04
Net Exports	-0.006	-0.44
Producer Price Index	-0.175**	-4.41
Consumer Price Index	-0.121*	-2.54
Housing Starts	-0.105**	-5.32
Index of Leading Ind.	-0.018	-0.67
Init. Unemployment Cl.	0.043 **	3.56

/ indicates significance at the 5%/1% level.*

Table 4: Return Regressions: Dual- vs. Broker-Intermediated Customer Flow

This table follows up on Table 3 and decomposes customer flow into dual- vs. broker-intermediated customer flow. It reports the estimation results of the following regression:

$$p_{t,h} - p_{t,h-1} = d_a(\alpha_a + \beta_a^d \omega_{t,h}^d + \beta_a^b \omega_{t,h}^b) + d_n(\alpha_n + \beta_n^d \omega_{t,h}^d + \beta_n^b \omega_{t,h}^b) + \sum_k \gamma_k I_{k,t} S_{k,t} + \varepsilon_{t,h}$$

where $p_{t,h}$ is 100 times the log price of the 30Y treasury futures at day t and five minute interval h, d_a (d_n) is a dummy that is one on an announcement (nonannouncement) day, zero otherwise, $\omega_{t,h}^d$ ($\omega_{t,h}^b$) is the aggregate signed customer volume intermediated by duals (brokers) divided by 1,000, $S_{k,t}$ is the announcement surprise, $I_{k,t}$ is a dummy that is one for the time interval immediately after the announcement, zero otherwise, and $\varepsilon_{t,k}$ is the error term. For estimation, we use the Feasible Efficient GMM procedure with a Newey-West estimator (using three lags) for standard errors. We report the estimates of the intercept and customer order flow coefficients estimated for 8:30-8:45 based on five minute intervals and tests for equality of customer order flow coefficients. We report t-values below coefficient estimates.

30Y Treasury Return Regressions, Dual- vs. Broker-Intermediated Customer Flow

				All Ann	Nonfarm, PPI, and CPI	Nonfarm Payroll Emp.
Customer Flow	Ann	Dual	β_a^d	0.0562**	0.0650**	0.0762**
				10.0	5.70	3.60
		Broker	β_a^b	0.0238*	0.0209	−0.0197
				2.53	1.27	−0.49
	Nonann	Dual	β_n^d	0.0265**	0.0265**	0.0265**
				8.92	8.92	8.92
		Broker	β_n^b	0.0230**	0.0230**	0.0230**
				4.77	4.77	4.77
Intercept	Ann		α_a	−0.0119**	−0.0367**	−0.0931**
				−2.79	−2.72	−3.23
	Nonann		α_n	0.0035*	0.0035*	0.0035*
				2.34	2.34	2.34
#Observations	Total			2,181	1,365	1,152
	Ann			1,131	315	102
	Nonann			1,050	1,050	1,050
R^2				0.375	0.366	0.396
p-value of $\mathrm{H_0}$:	$\beta_{\mathrm{a}}^{\mathrm{d}} = \beta_{\mathrm{n}}^{\mathrm{d}}$			0.0000**	0.0011**	0.0202*
	$\beta_{\mathrm{a}}^{\mathrm{b}} = \beta_{\mathrm{n}}^{\mathrm{b}}$			0.9400	0.9000	0.2880
	$\beta_{\mathrm{a}}^{\mathrm{d}} = \beta_{\mathrm{a}}^{\mathrm{b}}$			0.0036**	0.0343*	0.0628
	$\beta_{\mathrm{n}}^{\mathrm{d}} = \beta_{\mathrm{n}}^{\mathrm{b}}$			0.5110	0.5110	0.5110

/ indicates significance at the 5%/1% level.*

Table 5: Own-Account Trading Profits by Trader Type

This table reports summary statistics on the cross-sectional distribution of proprietary trading profits by trader type. We distinguish two types: those who also trade for customers on the same day, i.e. duals, and those who do not trade for customers on that day, i.e. locals. We follow Fishman and Longstaff (1992) and calculate the profits per contract traded round trip. That is, for each trader we subtract the value of purchases from the value of sales and add the value of end-of-period inventory (assuming zero inventory at the start). We divide this by the total number of contracts traded to arrive at a profit per contract traded round trip. Formally, we calculate:

$$\pi_{kt} = \left(\sum_{j=1}^{N^s_{kt}} q^s_{jkt} P^s_{jkt} - \sum_{j=1}^{N^b_{kt}} q^b_{jkt} P^b_{jkt} + (\sum_{j=1}^{N^b_{kt}} q^b_{jkt} - \sum_{j=1}^{N^s_{kt}} q^s_{jkt}) REFP_t \right) / \max(\sum_{j=1}^{N^b_{kt}} q^b_{jkt}, \sum_{j=1}^{N^s_{kt}} q^s_{jkt}),$$

where π_{kt} is the profit per round-trip contract for intermediary k on day t, N^b_{kt} (N^s_{kt}) is the total number of buys (sells), q^b_{jkt} (q^s_{jkt}) is the quantity of the jth transaction in terms of number of contracts, P^b_{jkt} (P^s_{jkt}) is the associated price, and $REFP_t$ is the reference price in day t. We assume any remaining inventory is valued at the last price before 8:45, thus $REFP_t$ is the last observed price before 8:45. We show the mean, standard deviation (*St Dev*) and the three quartiles (*25% Quant*, *Median* and *75% Quant*) of the cross-sectional distribution (across intermediaries) of own-account trading profits (with the number of trader days in each group in the column *#Trader Days*).

Own-Account Trading Profits per Contract Traded Round Trip						
	#Trader Days	Mean	St Dev	25% Quant	Median	75% Quant
Locals						
nonannouncement days	64,713	2.5	38.2	-13.5	0.0^{xx}	20.8
all announcement days	83,516	8.4	67.4	-13.2	$7.8^{**,xx}$	31.2
nonfarm, PPI, and CPI	25,301	17.0	93.0	-12.1	$14.8^{**,xx}$	43.9
nonfarm payroll emp.	8,242	26.7	117.8	-11.1	$23.7^{**,xx}$	62.5
Duals						
nonannouncement days	17,181	4.6	46.7	-15.6	2.2^{xx}	31.2
all announcement days	26,474	16.5	99.0	-13.4	$13.9^{**,xx}$	40.5
nonfarm, PPI, and CPI	8,381	29.6	142.2	-14.2	$22.8^{**,xx}$	62.5
nonfarm payroll emp.	2,709	49.0	199.1	-12.5	$31.3^{**,xx}$	101.6

/ indicates significance relative to nonannouncement days at the 5%/1% level.*

x/xx indicates significance relative to the other trader type at the 5%/1% level (i.e. a comparison across local and dual profit).

Table 6: Own-Account Trading Profits of Nonpure Duals and Pure Locals

This table reports own-account trading profits of nonpure duals, i.e. intermediaries who have both dual days (i.e. days they also trade for customers) and local days (i.e. days they do not trade for customers). Panel A reports cross-sectional statistics across all nonpure duals on the difference in average own-account profit for dual days and local days. Panel B reports cross-sectional statistics for the average own-account profit of nonpure duals on local days and similar statistics for the average own-account profit of pure locals (i.e. intermediaries that never trade for customers). To obtain own-account trading profits for each trader we subtract the value of purchases from the value of sales and add the value of end-of-period inventory (assuming zero inventory at the start). We divide this by the total number of contracts traded to arrive at a profit per contract traded round trip. Formally, we calculate:

$$\pi_{kt} = \left(\sum_{j=1}^{N_{kt}^s} q_{jkt}^s P_{jkt}^s - \sum_{j=1}^{N_{kt}^b} q_{jkt}^b P_{jkt}^b + \left(\sum_{j=1}^{N_{kt}^b} q_{jkt}^b - \sum_{j=1}^{N_{kt}^s} q_{jkt}^s\right) REFP_t \right) / \max\left(\sum_{j=1}^{N_{kt}^b} q_{jkt}^b, \sum_{j=1}^{N_{kt}^s} q_{jkt}^s\right),$$

where π_{kt} is the profit per round-trip contract for intermediary k on day t, N_{kt}^b (N_{kt}^s) is the total number of buys (sells), q_{jkt}^b (q_{jkt}^s) is the quantity of the jth transaction in terms of number of contracts, P_{jkt}^b (P_{jkt}^s) is the associated price, and $REFP_t$ is the reference price in day t. We assume any remaining inventory is valued at the last price before 8:45, thus $REFP_t$ is the last observed price before 8:45.

Panel A: Nonpure Duals' Profit Advantage on their Dual Days relative to their Local Days

Difference in Profits	All Days	Nonann Days	Ann Days
#Nonpure Duals	234	184	200
Mean Profit Advantage	8.6	2.8	13.5
Standard Deviation	59.1	35.9	68.0
25% Quantile	-8.3	-12.6	-10.2
Median	5.6	3.5	5.0
75% Quantile	24.6	14.7	34.7
%-age Coeff's positive	63.2	55.4	58.0
Test z-statistic[a]	4.05	1.47	2.26

[a] *Test statistic standard normal under H_0.*

Panel B: Trading Profits on Local Days, Pure Locals vs Nonpure Duals

	#Trader Days	Mean	St Dev	25% Quant	Median	75% Quant
Local Days of Pure Local						
nonannouncement days	33,083	2.8	37.4	-12.7	0.1	20.4
all announcement days	42,808	8.7	67.2	-13.6	7.8**	31.2
nonfarm, PPI, and CPI	18,499	16.7	90.2	-11.7	14.4**	42.7
nonfarm payroll emp.	6,911	26.5	115.8	-11.6	23.4**	61.7
Local Days of Nonpure Dual						
nonannouncement days	27,880	2.3	38.3	-13.9	0.0	20.8
all announcement days	36,061	8.5	67.4	-12.9	7.8**	31.2
nonfarm, PPI, and CPI	5,887	17.8	101.6	-13.5	15.6**	47.8
nonfarm payroll emp.	1,100	27.7	131.2	-7.8	25.2**	65.4

/ indicates significance relative to nonannouncement days at the 5%/1% level.*

x/xx indicates significance relative to the other trader type at the 5%/1% level (i.e. a comparison across local days of pure local and local days of nonpure dual profit).

Table 7: Determinants of Dual Trader's Own Account Profits on Announcement Days

This table reports the estimation results of the following regression:

$$\pi_{lt} = \alpha + \beta_1 CUST_{lt} + \beta_2 VOLA_t + \beta_3 COMP_t + \sum_k \gamma_k |S_{kt}| + \varepsilon_{lt}$$

where π_{lt} is dual l's own-account profit per round trip trade in the 15 minutes following the announcement on day t, $CUST_{lt}$ proxies for dual trader l's access to customer flow, $VOLA_t$ is the volatility measure, $COMP_t$ is a competition proxy and is defined as the ratio of the number of active intermediaries who trade for customers (i.e. dual and brokers) and the number of customer trades, S_{kt} is the macro surprise of announcement type k, and ε_{lt} is the error term. We use four proxies for a dual's access to customer order flow: the number of trades of dual l on day t that come from customers $\sum_j |D^c_{j,l,t}|$ (model (1)), the absolute value of the sum of the signed number of trades $|\sum_j D^c_{j,l,t}|$ (model (2)), the total quantity of dual l on day t that comes from customers $\sum_j Q^c_{j,l,t}$ (model (3)) and the absolute value of the sum of the signed quantity $|\sum_j D^c_{j,l,t} Q^c_{j,l,t}|$ (model (4)) where $D^c_{j,l,t}$ represents the direction (+1 for buy, -1 for sell) of trade j for trader l on day t. All regressors are demeaned to let the intercept represent the average trading profit per round trip in the 8:30-8:45 interval of a dual on an announcement day. For estimation, we use the Feasible Efficient GMM procedure with a Newey-West estimator (using three lags) for standard errors.

Dependent Variable: Dual's Trading Profit per Contract Traded Round Trip in the 8:30-8:45 interval on Ann Days												
	(1)	(1')	(1")[a]	(2)	(2')	(2")[a]	(3)	(3')	(3")[a]	(4)	(4')	(4")[a]
Proxies for $CUST_{lt}$												
trades												
$\sum_j \lvert D^c_{j,k,t}\rvert$	0.582**	0.233*	0.211**									
	5.06	2.03	3.3									
signed trades												
$\lvert\sum_j D^c_{j,k,t}\rvert$				1.13**	0.727**	0.726**						
				4.95	3.28	6.23						
quantity												
$\sum_j Q^c_{j,k,t}$							0.00358	−0.00150	−0.00159			
							1.45	−0.609	−1.13			
signed quantity												
$\lvert\sum_j D^c_{j,k,t} Q^c_{j,k,t}\rvert$										0.00668	−0.00118	−0.00143
										1.52	−0.271	−0.488
Intercept	16.5**	16.5**		16.5**	16.5**		16.5**	16.5**		16.5**	16.5**	
	26.2	26.8		26.2	26.9		26.1	26.8		26	26.8	
Control Variables												
volatility		2.86**			2.82**			3.02**			3.01**	
		3.13			3.09			3.25			3.24	
competition		−23.5			−24.1			−32.1**			−31.3*	
		−1.79			−1.88			−2.58			−2.51	
surprise?		yes			yes			yes			yes	
time dummy?			yes			yes			yes			yes
#Observations	26,474	26,474	26,474	26,474	26,474	26,474	26,474	26,474	26,474	26,474	26,474	26,474
R^2	0.004	0.017	0.039	0.004	0.018	0.040	0.000	0.016	0.039	0.000	0.016	0.039

/ indicates significance at the 5%/1% level.*

[a] *We use OLS instead of GMM as GMM estimation becomes too demanding numerically.*

Table 8: Customer Profits of Dual- vs. Broker-Intermediated Trades

This table reports customer trading profits of dual- and broker- intermediated customer trades, where dual traders also trade for own-account on that day and brokers do not. We follow Fishman and Longstaff (1992) and calculate the aggregate customer profits per contract traded round trip. That is, for each dual and broker trader we subtract the value of her customer purchases from the value of her customer sales and add the value of end-of-period inventory (assuming zero inventory at the start). We divide this by the total number of customer contracts traded to arrive at a profit per contract traded round trip. Formally, we calculate:

$$\pi_{kt} = \left(\sum_{j=1}^{N_{kt}^s} q_{jkt}^s P_{jkt}^s - \sum_{j=1}^{N_{kt}^b} q_{jkt}^b P_{jkt}^b + (\sum_{j=1}^{N_{kt}^b} q_{jkt}^b - \sum_{j=1}^{N_{kt}^s} q_{jkt}^s) REFP_t \right) / \max(\sum_{j=1}^{N_{kt}^b} q_{jkt}^b, \sum_{j=1}^{N_{kt}^s} q_{jkt}^s),$$

where π_{kt} is the customer profit per round-trip contract for intermediary k on day t, N_{kt}^b (N_{kt}^s) is the total number of customer buys (sells), q_{jkt}^b (q_{jkt}^s) is the quantity of the jth customer transaction in terms of number of contracts, P_{jkt}^b (P_{jkt}^s) is the associated price, and $REFP_t$ is the reference price in day t. We assume any remaining inventory is valued at the last price before 8:45, thus $REFP_t$ is the last observed price before 8:45. We show the mean, standard deviation (*St Dev*) and the three quartiles (*25% Quant*, *Median* and *75% Quant*) of the cross-sectional distribution (across intermediaries) of her customers' aggregate trading profits (with the number of trader days in each group in the column *#Trader Days*).

Customer Profits per Contract Traded Round Trip						
	#Trader Days	Mean	St Dev	25% Quant	Median	75% Quant
Dual-Intermediated Customer Trades						
nonannouncement days	17,181	-3.0	65.1	-32.5	0.0^{x}	31.3
all announcement days	26,474	-12.6	129.5	-67.7	$-7.3^{**,xx}$	49.0
nonfarm, PPI, and CPI	8,381	-22.7	175.8	-104.2	-17.5^{**}	63.5
nonfarm payroll emp.	2,709	-35.0	225.0	-147.1	-25.8^{**}	87.3
Broker-Intermediated Customer Trades						
nonannouncement days	6,567	-1.3	70.2	-31.3	0.0^{x}	31.3
all announcement days	9,034	-7.3	143.3	-62.5	$0.0^{**,xx}$	58.0
nonfarm, PPI, and CPI	2,843	-14.9	200.3	-101.7	-11.3^{**}	73.9
nonfarm payroll emp.	970	-23.2	250.9	-145.4	-19.3^{**}	94.1

/ indicates significance relative to nonannouncement days at the 5%/1% level.*

x/xx indicates significance relative to the other trader type at the 5%/1% level (i.e. a comparison across dual and broker aggregate customer profit).

Figure 1: Price and Volume of 30Y Treasury Futures on an Announcement Day

This figure depicts the prices of the 30Y treasury bond futures listed on the Chicago Board of Trade (CBOT) in the interval 8:20-9:00 on January 7, 1994. On this day there was an 8:30 Nonfarm Payroll Employment announcement. The top graph plots the volume-weighted average price for the second, where we use a circle (cross) if customer buying volume exceeds (falls below or equals) customer selling volume. The bottom figure plots the aggregate customer volume for every second.

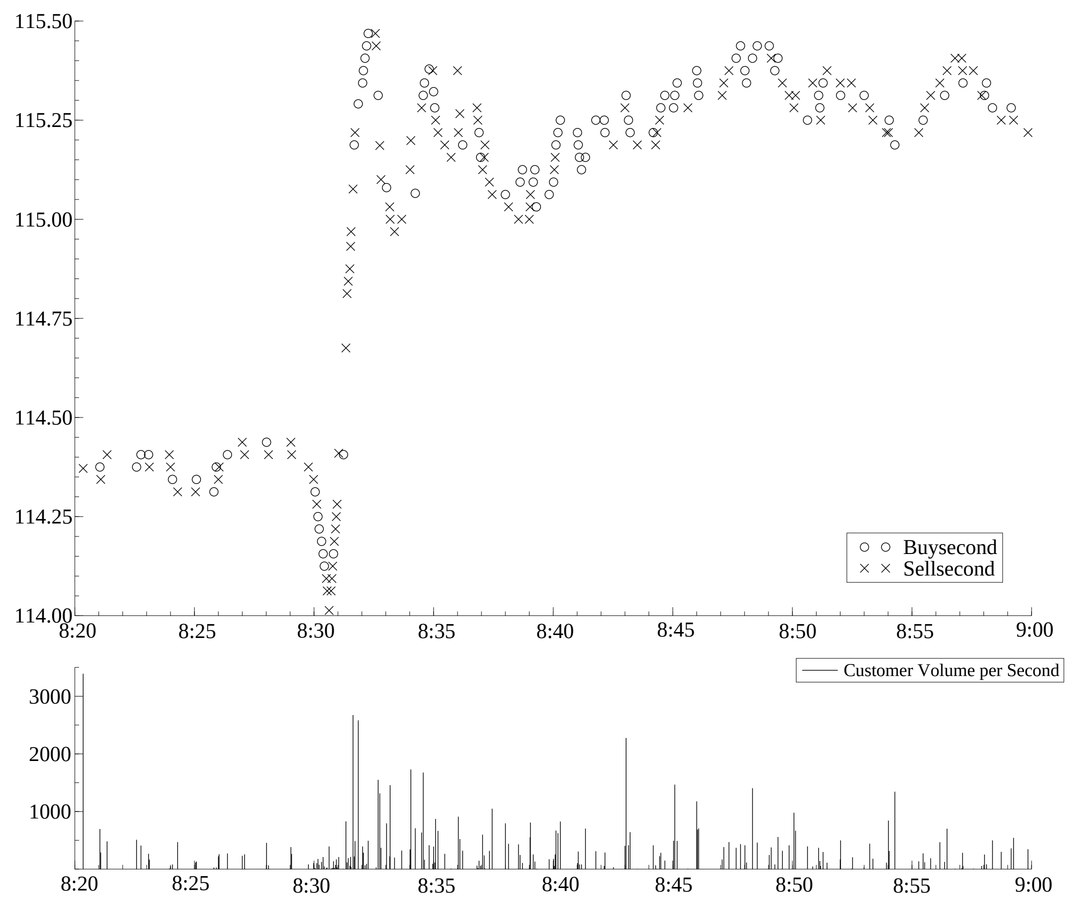

Figure 2: Intraday Trading Patterns

These figures depict intraday pattern of volatility (A), volume (B), and the bid-ask spread (C), based on fifteen minute intervals. The solid (dashed) lines show the intraday pattern for announcement (nonannouncement) days, the solid vertical lines represent the 8:30-8:45 announcement interval. An open (closed) circle indicates a significant difference between announcement and nonannouncement days at the 5% (1%) level.

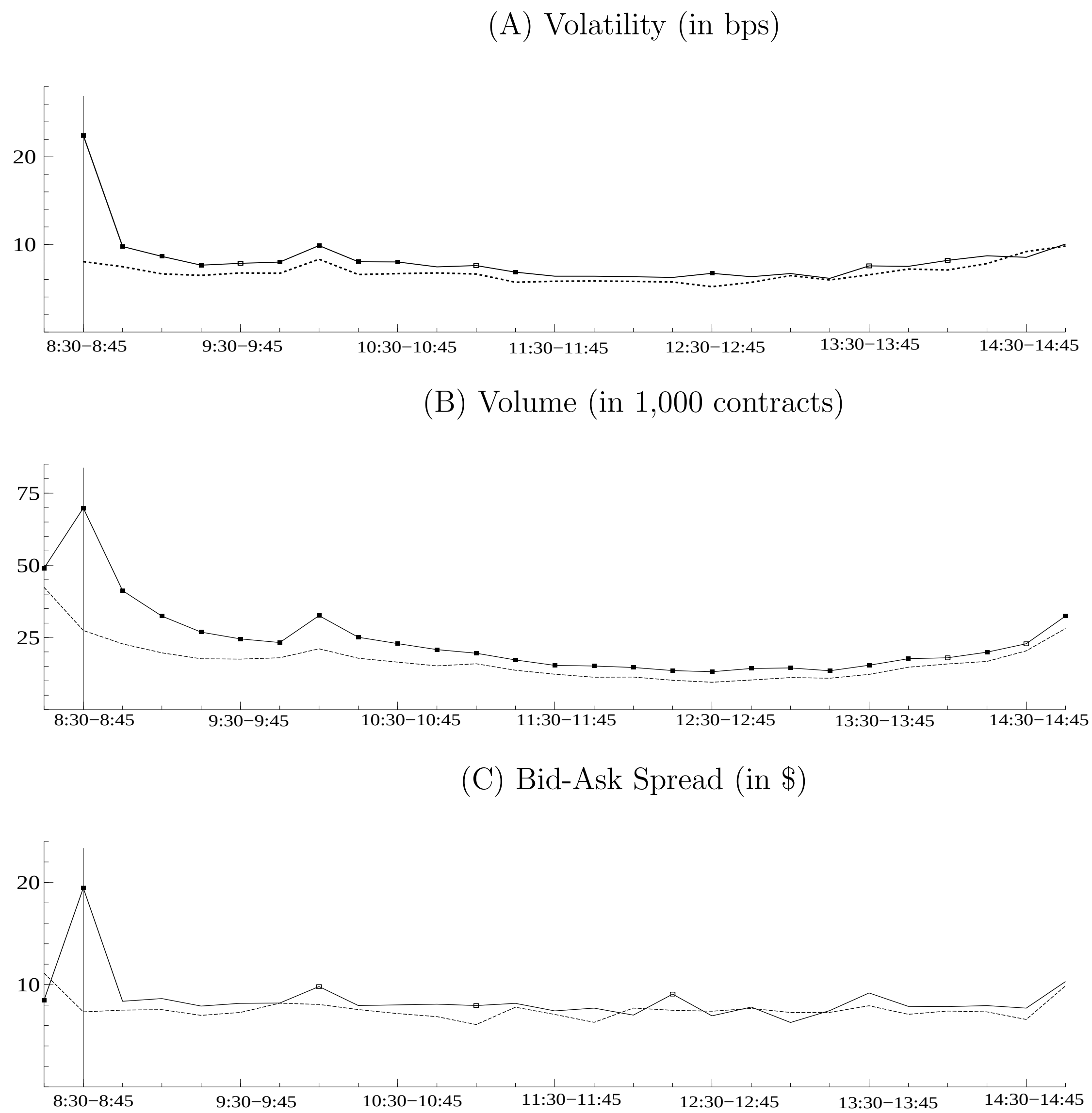

Figure 3: Intraday Pattern of Sensitivity of Treasury Return to Customer Flow
This figure depicts the coefficient of customer order flow in the 30Y treasury future return regressions. It plots this coefficient based on the estimation results of the following regression for all 15 minute intervals in the day:

$$p_{t,h} - p_{t,h-1} = d_a(\alpha_a + \beta_a \omega_{t,h}) + d_n(\alpha_n + \beta_n \omega_{t,h}) + \sum_k \gamma_k I_{k,t} S_{k,t} + \varepsilon_{t,h}$$

where $p_{t,h}$ is 100 times the log price of the 30Y treasury futures at day t and five minute interval h, d_a (d_n) is a dummy that is one on an announcement (nonannouncement) day, zero otherwise, $\omega_{t,h}$ is the aggregate signed customer volume, $S_{k,t}$ is the announcement surprise, $I_{k,t}$ is a dummy that is one for the time interval immediately after the announcement, zero otherwise, and $\varepsilon_{t,k}$ is the error term. For estimation, we use the Feasible Efficient GMM procedure with a Newey-West estimator (using three lags) for standard errors. The solid (dashed) line depicts the intraday pattern of β for announcement (nonannouncement) days; the vertical line represents the 8:30-8:45 announcement interval. An open (closed) circle indicates a significant difference between announcement and nonannouncement days at the 5% (1%) level.