CENTER FOR FINANCIAL STUDIES

No. 2008/47

Customer Flow, Intermediaries, and the Discovery of the Equilibrium Riskfree Rate

Albert J. Menkveld, Asani Sarkar, and Michel van der Wel

Center for Financial Studies
Goethe-Universität Frankfurt ■ House of Finance
Grüneburgplatz 1 ■ 60323 Frankfurt ■ Deutschland

Telefon: +49 (0)69 798-30050
Fax: +49 (0)69 798-30077
http://www.ifk-cfs.de ■ E-Mail: info@ifk-cfs.de

Center for Financial Studies

The *Center for Financial Studies* is a nonprofit research organization, supported by an association of more than 120 banks, insurance companies, industrial corporations and public institutions. Established in 1968 and closely affiliated with the University of Frankfurt, it provides a strong link between the financial community and academia.

The CFS Working Paper Series presents the result of scientific research on selected topics in the field of money, banking and finance. The authors were either participants in the Center´s Research Fellow Program or members of one of the Center´s Research Projects.

If you would like to know more about the *Center for Financial Studies*, please let us know of your interest.

Prof. Dr. Jan Pieter Krahnen

Prof. Volker Wieland, Ph.D.

Center for Financial Studies
Goethe-Universität ■ House of Finance
Grüneburgplatz 1 ■ 60323 Frankfurt am Main ■ Deutschland

Telefon: +49 (0)69 798-30050
Fax: +49 (0)69 798-30077
http://www.ifk-cfs.de ■ E-Mail: info@ifk-cfs.de

CFS Working Paper No. 2008/47

Customer Flow, Intermediaries, and the Discovery of the Equilibrium Riskfree Rate*

Albert J. Menkveld[1], Asani Sarkar[2],
and Michel van der Welt[3]

June 12, 2008

Abstract:
Macro announcements change the equilibrium riskfree rate. We find that treasury prices reflect part of the impact instantaneously, but intermediaries rely on their customer order flow in the 15 minutes after the announcement to discover the full impact. We show that this customer flow informativeness is strongest at times when analyst forecasts of macro variables are highly dispersed. We study 30 year treasury futures to identify the customer flow. We further show that intermediaries appear to benefit from privately recognizing informed customer flow, as, in the cross-section, their own-account trade profitability correlates with access to customer orders, controlling for volatility, competition, and the announcement surprise. These results suggest that intermediaries learn about equilibrium riskfree rates through customer orders.

JEL Classification: G14, E44

Keywords: Riskfree Rate, Macroeconomic Announcements, Customer Flow, Intermediary, Treasury Futures

* The views stated here are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of New York or the Federal Reserve System. The previous version had the title: “Macro News, Riskfree Rates, and the Intermediary: Customer Orders for 30Y Treasury Futures.” We appreciate the comments of Soehnke Bartram, Darrell Duffie, Michael Fleming, Thierry Foucault, Clifton Green, Terry Hendershott, Charles Jones, Richard Lyons, Bob Schwartz and participants at the “Microstructure of Equity and FX Markets” conference in Ottawa, the “International Conference on High Frequency Finance” conference in Konstanz, the Merton H. Miller doctoral seminar at the FMA2007, and a Federal Reserve Bank of New York seminar. We are grateful to the Netherlands Organization for Scientific Research (NWO) for a VENI grant and travel support. We are responsible for all errors. We are grateful for comments from Charlie Kahn, Jean-Charles Rochet and Jens Tapking and seminar participants at the Bank of England, the Cass Business School, the CEA meetings, the Bank of Canada, the Econometric Society Meetings, the SED meetings and the CEPR conference on Competition and Efficiency in Payment and Security Settlement Systems. Furthermore, we thank the Financial Markets Infrastructure Division at the Bank of England for their hospitality where some of this research was initiated. The usual disclaimers apply.

1 Corresponding Author. VU University Amsterdam, Tinbergen Institute, Roetersstraat 31, 1018 WB Amsterdam, The Netherlands; e-mail: albertjmenkveld@gmail.com

2 VU University Amsterdam, Tinbergen Institute

3 Federal Reserve Bank of New York

In frictionless markets, asset prices reflect public news instantaneously. We should therefore observe price changes only on announcements. Empirically, we see asset prices also change in the absence of announcements. This observation motivates the introduction of several market frictions to improve our understanding of asset price behavior and a prominent one is asymmetric information. That is, information is distributed asymmetrically across agents in the economy and the equilibrium price is learned through iterating over price quotes and updating based on the (aggregate) order imbalances that these prices provoke.[1] The market aggregates private information.

Recent evidence indicates that such private information is broader than the classic equity market interpretation of a private signal on a stock's future dividends. In the equity market itself, for example, the order flow is informative beyond the conjectured idiosyncratic effect as it contains a common factor that correlates with daily market returns.[2] Furthermore, order flow in nonequity markets, such as the currency and the treasury market, correlates significantly with permanent price changes.[3] Inspired by asset pricing models, the literature proposes that order flow conveys private information about the agent's optimization problem at the micro level, including her preferences and her endowments.[4]

Our main goal is to identify this source of information in the order flow—the part that captures the aggregation of private (micro) information from

[1]In *Eléments d'économie politique pure*, Walras (1889) first introduces the idea of tâtonnement, where agents submit buy (sell) orders when prices are low (high). Prices adjust to reflect the order imbalance until there are no additional orders. The equilibrium value has been discovered.

[2]See Hasbrouck and Seppi (2001). Edelen and Warner (2001) find correlated mutual fund flow to be part of this factor.

[3]See, e..g., Evans and Lyons (2002) and Evans and Lyons (2008) for the FX market and Brandt and Kavajecz (2004), Green (2004), and Pasquariello and Vega (2007) for the treasury bond market.

[4]See, e.g., Evans and Lyons (2002), Gallmeyer, Hollifield, and Seppi (2005), and Saar (2007).

the economy. The existing studies cannot identify this source for two reasons. First, they are based on interdealer flow which reflects customer order flow[5], but also contains dealer-initiated trades. These trades might reflect information other than the type we aim to identify, as some dealers might, for example, be superior information processors.[6] Also, dealers might initiate trades based on privately observing their customer identity, which endogenously biases dealer flow informativeness as a measure of customer flow informativeness. We elaborate on this flow-based speculation argument below. Second, existing studies do not control for a potential reverse causality due to "feedback trading" on stale prices. That is, public information arrives that causes the efficient price to change and, at the same time, agents trade against outstanding (stale) quotes that stand in the way of price adjustment. Hence, in the interval we witness a price change and trades in the direction of the change.

We turn to trading in 30-year treasury futures following macroeconomic announcements as an appropriate laboratory to identify private information aggregation in the economy for two main reasons. First, intermediaries have to report for-customer trades, which allows us to remove intermediary-initiated flow from the net order flow. Second, we observe the public signal—the macro "surprise"—and can therefore identify and remove the part of order flow that is feedback trading.

[5]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 aggregate interdealer market. See Lyons (1997) for a discussion of such "hot potato trading."

[6]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. Pan and Poteshman (2006) and Kurov and Lasser (2004) show that one potential source of such information is proximity to the aggregate order flow. By nature, this information is a short-lived (as dealers typically go home flat) whereas our focus is on the "long-lived" macro information that markets produce when aggregating micro customer flow.

Our results show that off-market customer flow is important for discovering the equilibrium riskfree rate. Relative to nonannouncement days, we find that customer flow is significantly more informative on price changes in the first 15 minutes after an announcement. Economically, the contribution of customer flow to price discovery is substantial as, after removal of the "feedback trading" part, it accounts for one-fourth of the (explained) riskfree rate change.[7] We further find that this informativeness increase is significantly larger for those months in which the dispersion in analyst forecasts is high. This suggests that intermediaries rely more heavily on customer flow at times of high disagreement on macro fundamentals.

Our finding provides further insight into the price discovery process in treasury markets. Prior studies also address the issue, but, unlike us, they use GovPX data that only covers interdealer flow and they are therefore unable to identify the origination of the information. For example, Ederington and Lee (1993) and Fleming and Remolona (1999) report a strong instantaneous response of treasury bond prices to an announcement, but also increased volatility in the minutes after the announcement. Green (2004) documents that in the first 15 minutes after the announcement treasury returns show increased sensitivity to order flow relative to the same time interval on nonannouncement days. Pasquariello and Vega (2007) find that the correlation increases with the dispersion in analyst forecasts.[8]

In addition to customer trade identification, our treasury futures sample has some attractive features. First, we do not need an algorithm to sign

[7] Specifically, we decompose the *increase* (relative to nonannouncement days) of the (explained) riskfree rate variance in the 15 minutes after the announcement and find that 76.0% is instantaneous and 24.0% is learned from customer flow.

[8] Pasquariello and Vega (2007) develop a model that predicts a liquidity improvement in the presence of a public signal (corollary 2 on p.1984). The prediction appears at odds with Green's findings, but the two can be reconciled if one allows for an increased rate of (exogenous) information arrival in the announcement interval. That is, the announcement itself makes agents re-optimize at the micro level and markets aggregate through order flow.

trades, as the data identifies for all customer transactions whether these customers buy or sell. Second, it is comprehensive as 30Y treasury futures capture 95% of the trading volume in the spot and futures markets for this maturity (see Fleming and Sarkar (1999)).

The second part of the paper generates further support for customer flow informativeness through an analysis of own-account profitability in the cross-section of intermediaries. The key idea is that the intermediary benefits from *privately* observing the identify of her customer. The futures exchange forbids any activity for own-account *ahead* of executing a client order on the floor, i.e. broker-dealers cannot frontrun a client order nor execute it (partially) against their own account (see Grossman (1989, p.6)).[9] As the origination of the order is not revealed in the trading process, after executing her client order the intermediary still benefits from having privately observed her customer identity by trading for own-account (on the floor) in same the direction as her customer if her customer was informed ("piggyback") and in the opposite direction if her customer was uninformed. The aggregate (i.e. customer plus own-account) net trade in the interdealer flow therefore amplifies the information part and reduces the noise part of the customer order. Zero-profit market makers rationally charge higher price impacts to protect themselves against such flow-based speculation, which thus endogenously biases interdealer flow informativeness as a measure of customer flow

[9]This institutional feature makes an alternative explanation for own-account profitability based on bargaining power in the spirit of Green, Hollifield, and Schürhoff (2007) unlikely.

informativeness.[10]

We exploit the large cross-section of 3,382 intermediaries and relate own-account profitability to customer flow access to provide direct evidence on flow-based speculation. We find two key results. First, we report that own-account profitability is higher for intermediaries who also trade for customers ("duals") relative to those who do not ("locals"). The benchmarking against locals serves to control for the increased cost of market-making in the volatile postannouncement period.[11] 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 ac-

[10]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.

[11]We find supportive evidence for such increased cost of market-making as a local's (gross) own-account profitability per round-trip trade is higher in the first 15 minutes after an announcement relative to profitability in the same period on nonannouncement days. We also find a significantly increased bid-ask spread in this period.

cess 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 increased profitability.[12]

We further analyze postannouncement trading to firmly 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, for an average announcement day five-minute interval, 172.9 intermediaries generate 595.9 transactions. Moreover, if we regress interest rate changes on only those customer orders that trade through intermediaries who do not trade for own-account that day, we find *unchanged* sensitivity.[13] Consistent with the flow-based speculation, it seems that intermediaries endogenously choose to trade for own-account on recognizing informed customers in their total customer flow.

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 interme-

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

[13] This is not an order size effect, as customer orders in this subset are larger than the average customer order.

diary 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 propose a model to illustrate 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. Our study differs in three ways. First, we focus on trading in the wake of a macro-announcement so as to control for a reverse causality caused by "feedback trading." We establish that customer flow is indeed informative. Second, we exploit a large cross-section of duals to establish that access to customer flow is a key determinant of own-account profitability. Third, we study a much larger sample (42.5 million trades in 4 years vs. 305,982 trades in 15 days) and benefit from statistical power which, for example, allows us to reject the alternative explanation based on trading skill, which could not be rejected in Fishman and Longstaff (1992).

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 increased profitability. 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 485.2 trades every five minutes on nonannouncement days and even more on announcement days.[14] Almost all trading is floor trading from 8.20 a.m. to 3.00 p.m. Eastern 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. An 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.[15] Today, dual trading continues to be allowed in most futures markets. The exceptions are some CME futures contracts, mostly those with a history of

[14] 345.9+112.3=485.2, see Table 2. Note that this table double-counts out of necessity, as we also report trade activity by trader type. We double-count throughout the paper in order to be consistent.

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

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[16]; 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[17] we restrict attention to CTI1 and CTI4 trades as they represent almost all trading volume.

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

[16]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).

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

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 (e.g. 9:15 or 10:00) to create benchmark nonannouncement days that are not contaminated by macro news trading.[18] 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.[19]

[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)).

Consistent with previous studies, we define announcement surprises as the difference between realizations and expectations (see, e.g., Green (2004) and Pasquariello and Vega (2007)). More specifically, since measurement units vary across macro variables, we standardize the surprises by dividing

[18]This also removes days with e.g. both an 8:30 *and* a 10:00 announcement. The remaining announcement days are therefore 8:30-only announcement days.

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

each of them by their sample standard deviation. The surprise S_{kt} of type k on day t is therefore

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

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 $(R_{kt} - M_{kt})$. Equation (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 customer volume imbalance on a representative macro announcement day. It illustrates some trading characteristics that will turn out to be true more generally. First, the 8:30 announcement leads to an instantaneous price change of almost 1%. Second, right after the announcement we observe increased (signed) customer volume imbalances which level off after roughly 15 minutes. Third, in this time period we observe large price changes that seem to correlate with the 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 nonannouncement 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 solid dot when the difference between announcement and nonannouncement days is significant at the 99% level.

Panel (A) shows that on announcement days, volatility is unchanged ahead of announcement, but significantly higher in the first half of the trading 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 only customer buy transaction prices[20] (see also Manaster and Mann (1996)). We find a significant spike 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 on a significantly increased bid-ask spread only 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 99% level in the first 15 minutes after the announcement. Economically, the increase is substantial as it exceeds 120%. We also find significantly increased volume ahead of the announcement on

[20] 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.

a significantly lower bid-ask spread, but these effects are small economically relative to postannouncement trading.

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 unique 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[21] 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 duals, i.e. customer trades through an intermediary who also trades for own account

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

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

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

[21] 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)).

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 42.4 intermediaries trade customer orders and 116.8 trade for own-account. They generate 112.3 and 345.9 trades, respectively. On announcement days, the number of active traders increases by approximately 20% and the number of transactions by 30%.

Panel A further disaggregates activity according to intermediary type and finds, for nonannouncement days, that the majority of active intermediaries acts as local (65%)[22], 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 vs. 7.9 brokers who carry out 21.4 customer transactions.[23] Trade size is larger for brokers, but even in terms of volume duals carry out most customer orders. Furthermore, the bid-ask spread is higher for customer trades through duals vs. 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 pro-

[22] 100%*81.4/(81.4+35.4+7.9).

[23] 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.

portional 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.[24]

Panel B presents the mean and standard deviation of five-minute signed customer volume in the 15 minutes after a macro announcement. These statistics are useful for our main analysis in the next section where we explore customer flow as an explanatory variable for 30Y treasury returns. The panel shows that, on average, customers are net buyers after an announcement but their net flow has a very large standard deviation relative to its mean. For the category of all announcement days, for example, we find that net customer flow is 0.142 with a standard deviation of 1.282. We decompose customer flow and find that dual-intermediated net flow is larger than broker-intermediated net flow. We find that net flow standard deviation on announcement days is higher than nonannouncement days and increases with the importance of the announcement.

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. Green (2004) documents empirical support as he finds an increased correlation between treasury returns and signed volume in the 15 minutes after an announcement. He cannot, how-

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

ever, identify that this information is in customer flow, as his signed volume is based on interdealer flow which, in addition to customer flow, also contains trades initiated by potentially superiorly informed intermediaries. In addition, the correlation might be endogenously biased upwards due to flow-based speculation by dual traders (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 any time-stamp errors might have. Consistent with previous studies, we add the macro surprise to the regression and estimate:

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

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,[25] 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

[25]In the implementation, we do allow for the surprise to also affect later time intervals (i.e. 8:35-8:40, 8:40-8:45, ...) and find no significance. For robustness, we nevertheless repeat all analysis based on equation (2) and find that our results are not affected.

other explanatory variables.[26] 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.

[insert Figure 3]

Figure 3 depicts the intraday pattern of customer flow informativeness on announcement as well as nonannouncement days. We estimate equation (2) separately for all 15-minute intervals in the trading day and test whether customer flow informativeness (β) is significantly different on announcement days relative to nonannouncement days.[27] 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 in these 15 minutes and the intraday pattern is therefore comparable—in shape and magnitude—to the bid-ask spread pattern.

[insert Table 3]

Panel A of Table 3 presents the results of a regression of returns on customer flow in the 15 minutes after the announcement (equation (2)). Although macro surprise coefficients (γ_k) are not reported for brevity, 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

[26] 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.

[27] For clarity, the d_a dummy of equation (2) is one for all five-minute intervals in a 15 minute period.

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 verify 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 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 this is the size of the part that correlates with the announcement surprise.[28] The economic significance of customer flow is further demonstrated by the result that a one standard deviation increase in net customer flow on announcement days (see Table 2) causes the 30Y treasury return to be 1.282*0.0439*100=6.3 basispoint higher, which is substantial relative to a 23

[28]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 (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 the explained variation on nonannouncement days to single out the effect due to the *increased* informativeness.

basispoint volatility for the *full* 15-minute return (see Figure 2).

Panel B of Table 3 finds that customer flow informativeness increases with the dispersion in analyst forecasts. Pasquariello and Vega (2007) find theoretically as well as empirically that correlation between order flow and yield changes should increase with the dispersion of beliefs among market participants. We follow their empirical approach and interact our customer flow variable with dummy variables that differentiates months with low, medium, and high analyst forecast dispersion. We find that, as expected, customer flow informativeness increases monotonically with dispersion. In our econometric tests on the coefficient differential across announcement and nonannouncement days, we find most significance for the high dispersion months, which is not surprising. In the joint test on the differential across all three forecast dispersion regimes, we find a significant differential only for the first two categories: (i) all announcements and (ii) the Nonfarm, PPI, and CPI announcements. It seems that we lack statistical power to also reject the null of no differential for the Nonfarm only announcements.

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.[29] 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 discriminating informed from uninformed customers, the intermediary's rational strategy is to trade along with

[29]We admit that the lack of significance for broker-intermediated flow might be the result of statistical power as in the average five-minute interval we find that the ratio of the number of active duals to the number of active brokers is roughly four (see Table 2). On the other hand, the sign of the differential of broker-intermediated customer flow across announcement days is wrong in two of the three cases.

informed customers and opposite to uninformed orders (see Appendix A).

3.1 Is direct access to customer flow profitable?

Inspired by Fishman and Longstaff (1992), 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 define profitability as:

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

where π_{kt} is the profit per round-trip contract[30] 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.[31] 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]

[30] We use a per-contract profit measure to control for trade activity, as locals are more active than duals.

[31] Available from the authors upon request.

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 95% (99%) level, whereas x (xx) indicates a significant difference between dual profitability and local profitability. We emphasize two important results.

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[32] \$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 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

[32]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).

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 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 have access (i.e. own-account profitability 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 rely on 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, and the difference is not statistically significant. For announcement days, we find a similar results as the profitability is \$7.8 and \$7.8, respectively, where again the difference is not significant. This higher profitability on announcement days is likely to reflect increased cost of market-making, e.g. due to higher inventory costs as result of higher volatility (see Figure 2). In sum, the insignificant difference between nonpure duals and locals suggests that idiosyncratic trading skill is not important in explaining cross-sectional differences in own-account trading profitability. Hence, this makes the alternative explanation for our results unlikely.

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 a dual trader's profit per contract in the 15 minutes of postannouncement trading on a measure of access to customer flow and various control variables:

$$\pi_{l,t} = \alpha + \beta_1 CUST_{l,t} + \beta_2 VOLA_t + \beta_3 COMP_t + \sum_k \gamma_k |S_{k,t}| + \varepsilon_{l,t} \qquad (4)$$

where $\pi_{l,t}$ is the profit per contract traded round trip of dual trader l in the 15 minutes of postannouncement trading on day t, $CUST_{lt}$ proxies for her access to customer flow in these 15 minutes (e.g., number of customer trades executed per contract traded round trip, $VOLA_t$ is our 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.[33] 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 dealer 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. This makes it generally harder to find a significant estimate of β_1.[34]

[insert Table 7]

Table 7 shows that a dual's own-account profitability increases with access to customer flow ($\beta_1 > 0$), but we only find strong significance if we use the signed customer trades proxy. We number the regression results based on the four proxies we use: number of trades, sum of signed trades, volume, and sum of signed volume. We use trades as well as volume to account for a 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 results show a positive coefficient for access to customer flow across all regressions and customer flow proxies, but we only find robust statistical significance for the signed customer trade proxy. Economically,

[33] We use the indicator l to relabel duals every day to minimize notational burden.

[34] 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.

the effect is substantial, as a one standard deviation increase in the signed trades proxy (1.94) earns the intermediary an additional 1.94*$2.76=$5.35 per contract on her own-account trades, which is a 39% increase relative to her $13.9 median profit on announcement days.[35] We further find, not surprisingly, that profits increase with volatility (e.g., to reflect more costly inventory keeping) and decrease with the level of competition.

The finding that the trade-based proxy shows stronger result than to the volume-based proxy is not surprising in view of the flow-based speculation argument. At first sight, the weak result on customer volume is counter-intuitive as one expects large customer orders to be more informative than small ones. Order size, however, is not private information to the intermediary as she has to execute the customer order on the floor before trading for own-account. So size, even though potentially informative, is not private information to her. Customer identity on the other hand is not revealed in the trading process and remains private information to the intermediary. It is therefore not surprising that having access to a multiplicity of customer orders is a key driver of own-account profitability rather than access to large customer orders.

4 Who pays for the dual's increased profit?

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

[35] See Table 2 and Table 7.

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 increased profit is paid for by her customers through an increased price concession that the market maker charges to protect herself against flow-based speculation. In an multiple intermediaries setting, who pays for the dual's increased profit 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 increased profit 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 increased profit.

4.1 Profitability of dual- and broker-intermediated customer orders

We analyze customer profits in the 15 minutes after the announcement to study whether dual-intermediated customers pay a disproportionate part of their intermediary's increased profit. 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 increased profit. 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. [36] This difference remains for the narrower sets of important announcements, but it is insignificant probably due to low power as the sample is considerably smaller. Our results differ from Fishman and Longstaff (1992) who find significantly higher profit for dual-intermediated customer flow, which is consistent with a model where a 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, on the other hand, 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). 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.

The negative customer profit result begs the question: Why customers do trade through duals if they seem to lose money? One possible explanation is that customers do not know ex-ante if their intermediary will dual trade that day or not. Fishman and Longstaff (1992) emphasize that the intermediary's decision is endogenous and depends on whether she receives informed customer flow. It is easily imaginable that this is a hard to predict event as informed investors have an incentive to randomize across intermediaries to hide their type as much as they can.

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

5 Conclusion

We exploit a comprehensive dataset of 42.5 million transactions in the 1994-1997 30Y treasury futures market that captures 95% of overall 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 8:30 macro announcement. This suggests that intermediaries rely on off-exchange customer orders 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 an important channel is off-exchange customer "response" to the news. The market appears to aggregate micro information on imperfectly known preferences and endowments throughout the economy (see, e.g., Saar (2007)).

We generate further evidence for customer flow informativeness through an analysis of own-account profitability in a large cross-section of 3,382 intermediaries. That is, if (i) customer flow is informative and if (ii) there is heterogeneity in order informativeness across customers, then observing customer identity is private information to the intermediary. In our market she has to trade her customer order on the floor before being able to trade for own-account, but customer identity does not have to be revealed on the floor. She therefore continues to benefit from having observed customer identity information and can trade on it *ex-post* for own account. We find supportive evidence for such flow-based speculation. First, we find that in the 15 minutes after the announcement, intermediaries with access to customer flow trade a significantly more profitable for own account than intermediaries without such access. The difference is a 78% higher median profit per contract. Second, among these intermediaries with access to customer flow, own-account profitability increases with access to signed customer trades.

Overall, our findings suggest that the trading process aggregates micro demand from off-exchange customers to discover macro variables such as the 30Y riskfree rate. This should give further empirical foundation to current macro models that build on agents' decisions at the micro level.

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:

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

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

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.

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

where $\omega = ((\alpha+\beta)v + (1+\gamma)u)$ is the aggregate order the market maker receives. Equation (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.

References

Anand, A., and A. Subrahmanyam. 2007. "Information and the intermediary: Are market intermediaries informed traders in electronic markets?" *Journal of Financial and Quantitative Analysis (forthcoming).*

Beneviste, L.M., A.J. Marcus, and W.J. Wilhelm. 1992. "What's so Special about the Specialist?" *Journal of Financial Economics* 32:61–86.

Brandt, M.W., and K.A. Kavajecz. 2004. "Price Discovery in the U.S. Treasury Market: The Impact of Orderflow and Liquidity on the Yield Curve." *Journal of Finance* 59:2623–2654.

Chakravarty, S., and K. Li. 2003. "An Examination of Own Account Trading by Dual Traders in Futures Markets." *Journal of Financial Economics* 69:1–42.

Chang, E.C., P.R. Locke, and S.C. Mann. 1994. "The Effect of CME Rule 552 on Dual Traders." *Journal of Futures Markets* 14:493–510.

Chung, K.H., C. Chuwonganant, and D.T. McCormick. 2004. "Order preferencing and market quality on NASDAQ before and after decimalization." *Journal of Financial Economics* 71:581–612.

Easley, D., N.M. Kiefer, and M. O'Hara. 1996. "Cream-Skimming or Profit-Sharing? The Curious Role of Purchased Order Flow." *Journal of Finance* 51:811–833.

Edelen, R.M., and J.B. Warner. 2001. "Aggregate Price Effects of Institutional Trading: A Study of Mutual Fund Flow and Market Returns." *Journal of Financial Economics* 59(1):195–220.

Ederington, L., and J. Lee. 1993. "How Markets Process Information: News Releases and Volatility." *Journal of Finance* 45:1161–1191.

Evans, M.D.D., and R.K. Lyons. 2002. "Orderflow and Exchange Rate Dynamics." *Journal of Political Economy* 110:170–180.

———. 2008. "How is Macro News Transmitted to Exchange Rates?" *Journal of Financial Economics* 88:26–50.

Fishman, M.J., and F.A. Longstaff. 1992. "Dual Trading in Futures Markets." *Journal of Finance* 47(2):643–671.

Fleming, M.J., and E.M. Remolona. 1999. "Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information." *Journal of Finance* 54:1901–1915.

Fleming, M.J., and A. Sarkar. 1999. "Liquidity in U.S. Treasury Spot and Futures Markets." *Market Liquidity Research Findings and Selected Policy Implications, Bank for International Settlements.*

Gallmeyer, M.F., B. Hollifield, and D.J. Seppi. 2005. "Demand Discovery and Asset Pricing." Technical Report, Carnegie Mellon University. AFA 2005 Paper.

Green, R.C., B. Hollifield, and N. Schürhoff. 2007. "Financial Intermediation and the Costs of Trading in an Opaque Market." *Review of Financial Studies* 20:275–314.

Green, T.C. 2004. "Economic News and the Impact of Trading on Bond Prices." *Journal of Finance* 59:1201–1233.

Grossman, S.J. 1989. "An Economic Analysis of Dual Trading." Technical Report, Rodney L. White Center Working Papers #33-89, Wharton School.

Hasbrouck, J., and D.J. Seppi. 2001. "Common Factors in Prices, Order Flows, and Liquidity." *Journal of Financial Economics* 59:383–411.

Kim, O., and R.E. Verrecchia. 1994. "Market Liquidity and Volume around Earnings Announcements." *Journal of Accounting and Economics* 17:41–67.

———. 1997. "Pre-Announcement and Event-Period Information." *Journal of Accounting and Economics* 24:395–419.

Kurov, A., and D.J. Lasser. 2004. "Price Dynamics in the Regular and E-Mini Futures Markets." *Journal of Financial and Quantitative Analysis* 39:365–384.

Kyle, A. 1985. "Continuous Auctions and Insider Trading." *Econometrica* 53:1315–1335.

Lyons, R. 1997. "A Simultaneous Trade Model of the Foreign Exchange Hot Potato." *Journal of International Economics* 42:275–298.

Madrigal, V. 1996. "Non-Fundamental Speculation." *Journal of Finance* 51(2):553–576.

Manaster, S., and S.C. Mann. 1996. "Life in the Pits: Competitive Market Making and Inventory Control." *Review of Financial Studies* 9(3):953–975.

Pan, J., and A.M. Poteshman. 2006. "The Information in Option Volume for Future Stock Prices." *Review of Financial Studies* 19:871–908.

Pasquariello, P., and C. Vega. 2007. "Informed and Strategic Order Flow in the Bond Market." *Review of Financial Studies (forthcoming)*.

Roell, Ailsa. 1990. "Dual-Capacity Trading and the Quality of the Market." *Journal of Financial Intermediation* 1:105–124.

Saar, G. 2007. "Systematic Liquidity and Learning about the Risk Premium." Technical Report, Cornell University.

Wahal, S. 1997. "Entry, Exit, Market Makers, and the Bid-Ask Spread." *Review of Financial Studies* 10(3):871–901.

Walras, L. 1889. *Elements d'Economique Politique Pure, ou Theorie de la Richesse Sociale*. Lausanne: Rouge.

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 and Signed Customer Volume (CTI4)
In Panel A, we show the average number of traders active, number of transactions, trade size (in #contracts) and bid-ask spread (in $) per five minute interval for the 30Y treasury futures listed on the Chicago Board of Trade (CBOT) on both announcement and nonannouncement days. The averages are taken over the full day in five minute intervals, we show the variables 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%. In Panel B we show statistics for the signed customer volume (CTI4, in 1,000 contracts). We show mean and standard devation (*St Dev*) for five minute intervals as calculated for 8:30-8:45. We split the aggregate signed customer volume to the dual- and broker-intermediated parts. The sample consists of all trading days in the period 1994 through 1997.

Panel A: Trade Statistics by Trader Type (five min avg, full day)						
	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 (in #contracts)	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)).*

Panel B: Signed Customer Volume (CTI4) Statistics (five min avg, 8:30-8:45)						
			All Ann	Nonfarm, PPI, and CPI	Nonfarm Payroll Emp.	Nonann
Signed Customer Volume (CTI4) (in 1,000 contracts)	Mean	All	0.142^{**}	0.301^{**}	0.213	0.058^{*}
		Dual	0.108^{**}	0.224^{**}	0.122	0.010
		Broker	0.034	0.077	0.091	0.048^{**}
	St Dev	All	1.282	1.658	1.789	0.740
		Dual	1.164	1.477	1.622	0.663
		Broker	0.648	0.888	0.872	0.413

/ indicates mean significant different from zero at the 95%/99% level.*

Table 3: Regressions of 30Y Treasury Return on Signed Customer Volume (CTI4)

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 (CTI4) 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 signed customer volume coefficients estimated for 8:30-8:45 based on five minute intervals and tests for equality of signed customer volume coefficients. In Panel B we split the estimated signed customer volume coefficients for the sample of all announcement days in three groups based on dispersion of beliefs. In particular, we follow Pasquariello and Vega (2007) and estimate the coefficients for days with high, medium and low dispersion of beliefs. High (low) dispersion is defined as the monthly forecasts' standard deviation to be in the top 70th (bottom 30th) percentile of its empirical distribution. The monthly forecasts' standard deviation is based on the standard deviation of forecasts for all available 8:30 announcements. We report t-values below coefficient estimates.

Panel A: 30Y Treasury Return Regressions

			All Ann	Nonfarm, PPI, and CPI	Nonfarm Payroll Emp.
Signed Cust-	Ann	β_a	0.0493^{**}	0.0544^{**}	0.0571^{**}
			10.4	6.06	3.77
omer Volume (CTI4)	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 95%/99% level.*

(continued on next page)

(continued from previous page)

Panel B: 30Y Treasury Return Regressions with Dispersion of Beliefs						
				All Ann	Nonfarm, PPI, and CPI	Nonfarm Payroll Emp.
Signed Customer Volume (CTI4)	Ann	High Het	$\beta_{a,H}$	0.0596^{**} 7.14	0.0677^{**} 4.41	0.0643^{*} 2.19
		Med Het	$\beta_{a,M}$	0.0489^{**} 7.32	0.0611^{**} 4.5	0.0742^{**} 2.99
		Low Het	$\beta_{a,L}$	0.0365^{**} 3.26	0.0290 1.53	0.0169 0.443
	Nonann	High Het	$\beta_{n,H}$	0.0285^{**} 6.34	0.0285^{**} 6.34	0.0285^{**} 6.34
		Med Het	$\beta_{n,M}$	0.0303^{**} 7.96	0.0303^{**} 7.96	0.0303^{**} 7.96
		Low Het	$\beta_{n,L}$	0.0163^{**} 3.04	0.0163^{**} 3.04	0.0163^{**} 3.04
Intercept	Ann		α_a	-0.0119^{**} -2.8	-0.0363^{**} -2.68	-0.0948^{**} -3.28
	Nonann		α_n	0.0033^{*} 2.27	0.0033^{*} 2.27	0.0033^{*} 2.27
#Observations	Total			2,181	1,365	1,152
	Ann			1,131	315	102
	Nonann			1,050	1,050	1,050
R^2				0.369	0.361	0.378
p-value of H_0:	$\beta_{a,H} = \beta_{n,H}$			0.0010^{**}	0.0142^{*}	0.2270
	$\beta_{a,M} = \beta_{n,M}$			0.0157^{*}	0.0289^{*}	0.0801
	$\beta_{a,L} = \beta_{n,L}$			0.1040	0.5190	0.9880
	$\beta_{a,d} = \beta_{n,d}, d = H, M, L$			0.0002^{**}	0.0102^{*}	0.1670

/ indicates significance at the 95%/99% level.*

Table 4: Return Regressions: Dual- vs. Broker-Intermediated Signed Customer Volume (CTI4)

This table follows up on Table 3 and decomposes signed customer volume (CTI4) into dual- vs. broker-intermediated signed customer volume. 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 (CTI4) 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 signed customer volume coefficients estimated for 8:30-8:45 based on five minute intervals and tests for equality of signed customer volume coefficients. We report t-values below coefficient estimates.

Return Regressions, Dual- vs. Broker-Intermediated Signed Customer Volume (CTI4)

				All Ann	Nonfarm, PPI, and CPI	Nonfarm Payroll Emp.
Signed Cust-	Ann	Dual	β_a^d	0.0562^{**}	0.0650^{**}	0.0762^{**}
				10.0	5.70	3.60
omer Volume (CTI4)		Broker	β_a^b	0.0238^{*}	0.0209	-0.0197
				2.53	1.27	-0.494
	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 H_0:	$\beta_a^d = \beta_n^d$			0.0000^{**}	0.0011^{**}	0.0202^{*}
	$\beta_a^b = \beta_n^b$			0.9400	0.9000	0.2880
	$\beta_a^d = \beta_a^b$			0.0036^{**}	0.0343^{*}	0.0628
	$\beta_n^d = \beta_n^b$			0.5110	0.5110	0.5110

/ indicates significance at the 95%/99% level.*

Table 5: Own-Account Trading Profits by Trader Type

This table reports summary statistics on the cross-sectional distribution of proprietary trading profits in the 8:30-8:45 interval 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:

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

where π_{kt} is the 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. 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 95%/99% level.*

x/xx indicates significance relative to the other trader type at the 95%/99% 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 in the 8:30-8:45 interval 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:

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

where π_{kt} is the 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 95%/99% level.*
x/xx indicates significance relative to the other trader type at the 95%/99% 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 flow (CTI4): 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 customer trades $|\sum_j D^c_{j,l,t}|$ (model (2)), the total volume 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 volume $|\sum_j D^c_{j,l,t} q^c_{j,l,t}|$ (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. We scale the proxies for access to customer flow $CUST_{lt}$ with the number of round trips (#RndTrips$_{l,t}$) for each dual l on each day t as this is also done for our profits measure π_{lt}. 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")	(2)	(2')	(2")	(3)	(3')	(3")	(4)	(4')	(4")
Proxies for $CUST_{lt}$												
customer trades												
$\sum_j \lvert D^c_{j,l,t}\rvert$/#RndTrips$_{l,t}$	1.07**	0.646	0.600									
	3.1	1.9	1.75									
signed customer trades												
$\lvert\sum_j D^c_{j,l,t}\rvert$/#RndTrips$_{l,t}$				3.14**	2.64**	2.76**						
				4.44	3.82	3.78						
customer volume												
$\sum_j q^c_{j,l,t}$/#RndTrips$_{l,t}$							0.0218	0.00926	0.00744			
							1.59	0.653	0.514			
signed customer volume												
$\lvert\sum_j D^c_{j,l,t} q^c_{j,l,t}\rvert$/#RndTrips$_{l,t}$										0.0656*	0.0459	0.0444
										2.16	1.47	1.45
Intercept	16.5**	16.5**		16.5**	16.5**		16.5**	16.5**		16.5**	16.5**	
	26.1	26.9		26.1	26.9		26	26.8		26.1	26.8	
Controls												
volatility		2.93**			2.87**			3.00**			3.00**	
		3.18			3.12			3.24			3.23	
competition		-28.0^{*}			-28.0^{*}			-30.5^{*}			-30.2^{*}	
		-2.22			-2.23			-2.44			-2.42	
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	0.002	0.017	0.040	0.004	0.019	0.042	0.000	0.016	0.039	0.000	0.016	0.040

/ indicates significance at the 95%/99% level.*

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

This table reports customer trading profits in the 8:30-8:45 interval 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:

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

where π_{kt} is the customer profit per round-trip contract for intermediary k on day t, N^b_{kt} (N^s_{kt}) is the total number of customer buys (sells), q^b_{jkt} (q^s_{jkt}) is the quantity of the jth customer 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 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 95%/99% level.*
x/xx indicates significance relative to the other trader type at the 95%/99% 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 May 3, 1996. 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 signed customer volume (CTI4) for every second.

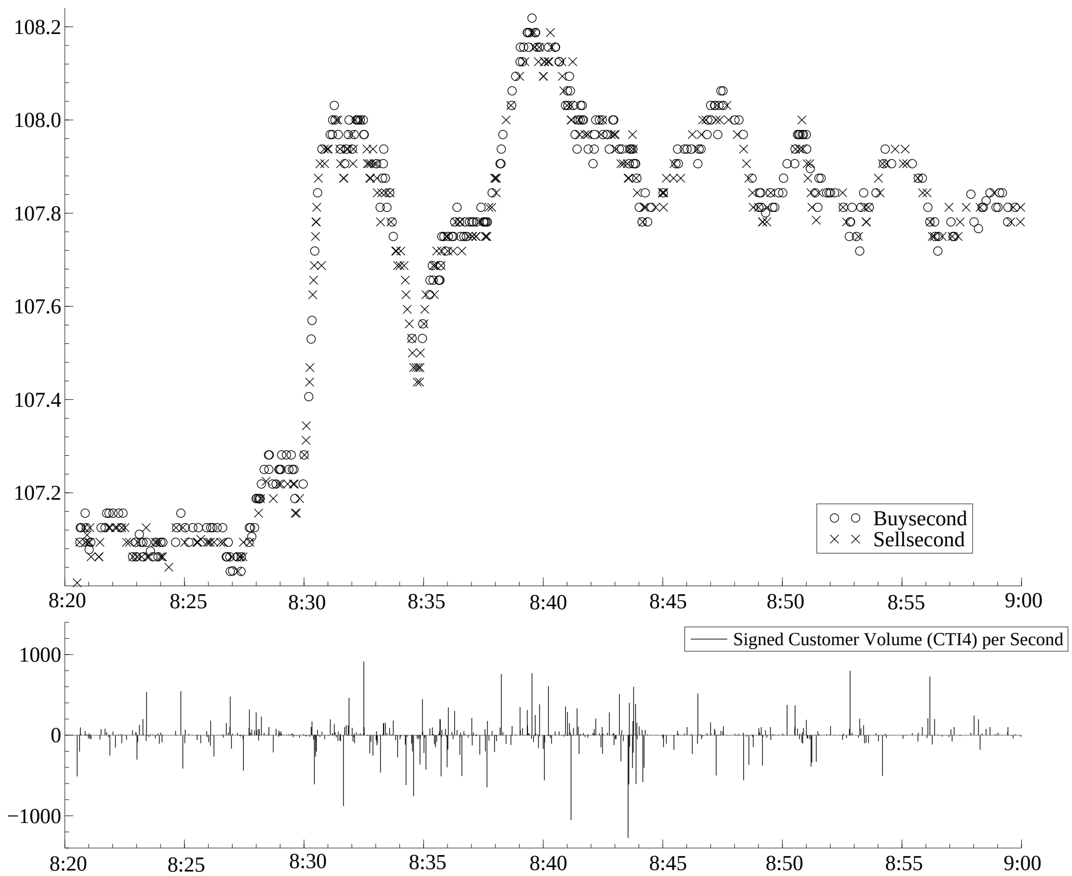


Figure 2: Intraday Trading Patterns

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. A closed circle indicates a significant difference between announcement and nonannouncement days at the 99% level.

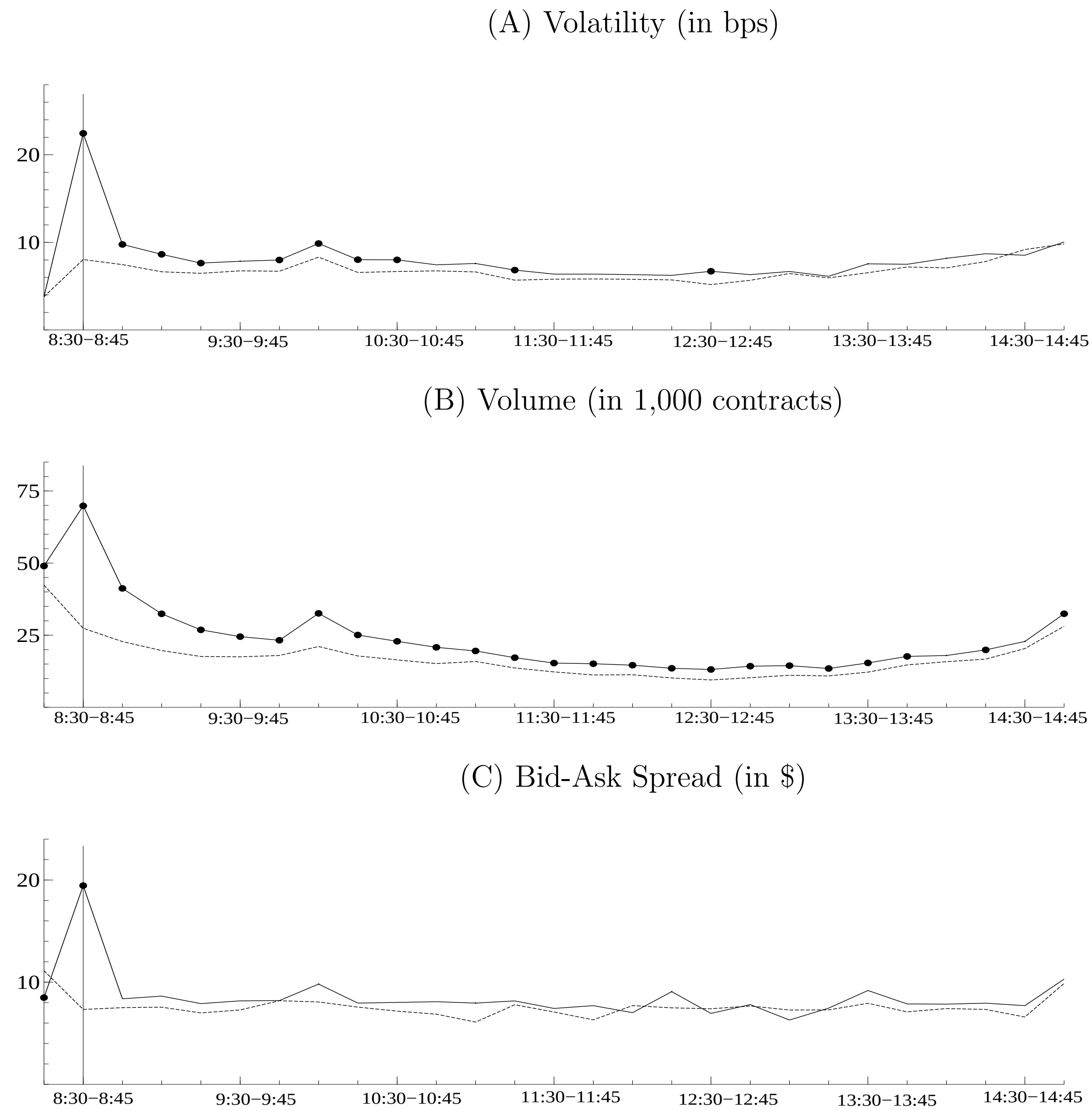
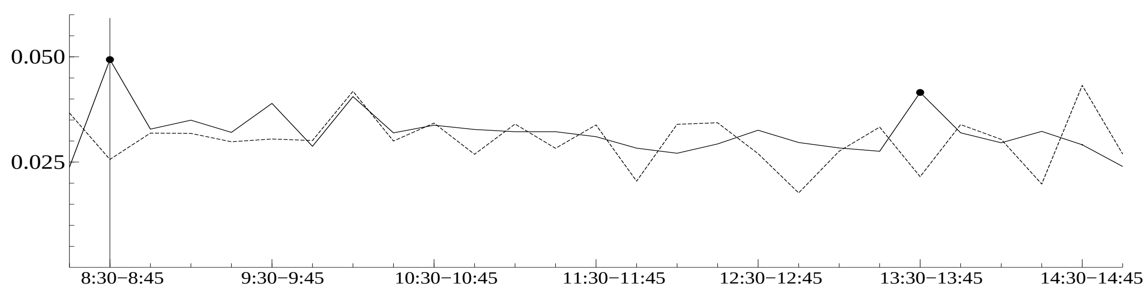


Figure 3: Intraday Pattern of Sensitivity of Treasury Return to Signed Customer Volume (CTI4)

This figure depicts the coefficient of signed customer volume (CTI4) 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 (CTI4), $S_{k,t}$ 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. A closed circle indicates a significant difference between announcement and nonannouncement days at the 99% level.



CFS Working Paper Series:

No.	Author(s)	Title
2008/46	**Mark Van Achter**	A Dynamic Limit Order Market with Diversity in Trading Horizons
2008/45	**Michael S. Pagano** **Lin Peng** **Robert A. Schwartz**	The Quality of Price Formation at Market Openings and Closings: Evidence from the Nasdaq Stock Market
2008/44	**David Reiffen** **Michel Robe**	Demutualization and Enforcement Incentives at Self-regulatory Financial Exchanges
2008/43	**Craig Pirrong**	The Industrial Organization of Execution, Clearing and Settlement in Financial Markets
2008/42	**Thorsten V. Koeppl** **Cyril Monnet**	Central Counterparties
2008/41	**Terrence Hendershott** **Charles M. Jones** **Albert J. Menkveld**	Does Algorithmic Trading Improve Liquidity?
2008/40	**Jonathan Field** **Jeremy Large**	Pro-Rata Matching and One-Tick Futures Markets
2008/39	**Giovanni Cespa** **Thierry Foucault**	Insiders-Outsiders, Transparency and the Value of the Ticker
2008/38	**Rachel J. Huang** **Alexander Muermann** **Larry Y. Tzeng**	Hidden Regret in Insurance Markets: Adverse and Advantageous Selection
2008/37	**Alexander Muermann** **Stephen H. Shore**	Monopoly Power Limits Hedging

Copies of working papers can be downloaded at http://www.ifk-cfs.de