Do Brokers Misallocate Customer Trades?
Evidence from Futures Markets

Hun Y. Park, Asani Sarkar and Lifan Wu

Hun Y. Park
Department of Finance
University of Illinois at Urbana-Champaign

Asani Sarkar
Research Department
The Federal Reserve Bank of New York

Lifan Wu
City University of Hong Kong

OFOR Paper Number 98-01
January 1998

Do Brokers Misallocate Customer Trades?
Evidence from Futures Markets

Hun Y. Park
Department of Finance
University of Illinois at Urbana-Champaign
Champaign, IL 61820
217-333-0659
E-mail: h-park 3@uiuc.edu

Asani Sarkar
The Federal Reserve Bank of New York
Research Department
33 Liberty Street
New York, NY 10045
212-720-8943
fax: 212-720-1582
EMAIL: asani.sarkar@ny.frb.org

Lifan Wu
City University of Hong Kong
83 Tat Chee Avenue
Kowloon, Hong Kong
Fax: 8522-788-8806
EMAIL: efcwu@cityu.edu.hk

Current version: December 1997
Previous version: November 1997

We are grateful to the Commodity Futures Trading Commission and the Chicago Mercantile Exchange for the provision of data. The views stated herein 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. We thank Louis Chan, James Moser and two anonymous referees for comments. We are responsible for all errors.

Abstract

Do Brokers Misallocate Customer Trades?
Evidence from Futures Markets

JEL Classification number: G12, G13, G18

In the context of futures markets, we study whether brokers allocate more favorable trades to their own accounts, and less favorable trades to their customers. We find that, within a thirty minute trading bracket, brokers on average buy at a lower price and sell at a higher price for their own accounts relative to their customers. We show evidence that brokers' price advantage may be compensation for providing liquidity to the market when brokers trade for their own accounts, but no evidence that they are due to brokers' superior information, or to greater effort by brokers when trading for themselves. Consistent with the idea that, in a competitive market for brokerage services, brokers may pass on some of their profits to customers, we find that brokers who trade for themselves also provide superior execution for their customers, relative to brokers who do not trade for themselves.

Do Brokers Misallocate Customer Trades?
Evidence From Futures Markets

When brokers trade for their own accounts, in addition to trading for customers, there is a potential for trading abuse. One such abuse is misallocation, whereby brokers reserve the best prices for their own trades and allocate trades with inferior prices to their customers. For example, the Commodity Futures Trading Commission (CFTC) recently charged a broker for "fraudulently allocating trades among his personal account and his three customer accounts to his benefit and to the detriment of his customers." The broker in question entered orders, but not account numbers, to the trading floor. When the orders were filled, they were allocated either to the broker's account number or his three customers' accounts, depending on fill quality.[1]

The General Accounts Office (GAO, 1989a, 1989b) reported cases in futures markets where customers received worse prices than existing best bids and offers, and commented that brokers' trading facilitated such practices.[2] The New York Stock Exchange (NYSE), in 1995, fined Goldman, Sachs & Co. $250,000 for "assigning to the firm trades at prices more favorable than those assigned to institutional customers." In one case, Goldman, after receiving customer orders to buy shares at $20.50 each, bought shares at prices of $20.50 and $20.25 within a three minute period. NYSE argued that Goldman should have offered the customer shares it bought for $20.25, instead of $20.50, which is the amount it actually charged customers.[3]

Economists may not necessarily interpret some of the trade practices described above as

[1]CFTC Enforcement Action 4023-97 (CFTC Docket No. 97-8).

[2]However, the GAO also stated that banning brokers' trading would not solve the problem, since brokers who do not trade personally can also commit abuses by working together. Currently, brokers' trading is banned in most active US futures markets (also see footnote five on this issue).

[3]The *Wall Street Journal*, February 17 1995, page C1.

detrimental to customer welfare. Instead, they may argue, the difference in prices received by customers and brokers is an implicit bid-ask spread, required to compensate brokers for their market making activities. For example, in the Goldman case, traders may have searched and received a better price than initially targeted by the customer. Arguably, Goldman could have sold to customers at a price of (say) $20.375, keeping a "spread" of $0.125 per share for itself. Although this price difference could technically constitute misallocation, customers may receive a service worth $0.125 per share.

Economists may also argue that, given a competitive market for brokerage services, "discriminated" customers are likely to be compensated in some other form---through lower commissions (as predicted, in the context of front running, by Fishman and Longstaff (1992)), or better quality executions.

In this paper, we address these issues by analyzing the behavior of floor traders in futures markets who practice dual trading (i.e., trade for their personal accounts in addition to trading for their customers in the same futures contract during the same day).[4] The potential for trading abuses has spurred regulatory scrutiny of dual trading, culminating in the Futures Trading Practices Act of 1992, which required the CFTC to establish rules banning dual trading in all active futures markets.[5]

---

[4]This trading practice had been pervasive across securities markets until 1991, when it was partially banned in some futures markets. See Grossman (1989) for a detailed description of the practice of dual trading in the securities markets in the United States and other countries.

[5] The law allows an exemption if the exchange adequately improves audit trails. Five exchanges have requested exemptions. So far, only the Comex Division (Comex) of the New York Mercantile Exchange and the Chicago Mercantile Exchange's (CME) S&P 500 futures contract have received unconditional exemptions from the dual trading ban. Seven other CME contracts and 13 contracts at the Chicago Board of Trade have received a conditional exemption allowing dual trading in low volume months only. See CFTC press releases, May 7, 1997 and November 7, 1997.

We construct a two period microstructure model to illustrate how brokers may misallocate customer trades. In the model, an informed customer and noise traders trade through a broker in period one. The broker trades in period two based on information derived from customer orders. The possibility of misallocation exists because the prices in the two periods are different, providing the broker an incentive to allocate more favorable trades to himself. We show that the incentive to misallocate trades is increasing in price volatility and market uncertainty, and decreasing in the size of uninformed trades. We further show that brokers' legitimate trading profits per futures contract decrease with a trade's price impact, but their profits per contract from misallocation increase with the price impact. Finally, we show that dual trading brokers may provide larger price discounts than non-trading brokers, given a competitive market for brokerage services.

To empirically test for the existence of misallocation, we use a detailed data set consisting of all transactions by dual traders, both for their own and their customers' accounts, in the S&P 500 index futures and the Japanese yen futures pits for fifteen randomly selected days in 1987. Table 1 provides an overview of our tests and results. Our analysis shows that, for both contracts, brokers receive better prices for their own trades than for their customers' trades. However, brokers' price advantage in both contracts may be compensation for liquidity services provided by brokers when trading for their own accounts. Further, for the S&P 500 futures, brokers appear to pass on a portion of their price advantage by providing superior execution to their customers.

Specifically, we find that, within a thirty minute trading bracket, dual traders in both contract markets buy at a lower price and sell at a higher price, on average, when trading for their own accounts than when trading for customers. A possible explanation of the price differences is that they reflect dual traders' compensation for providing market making services to their customers. Kuserk and Locke (1993), Silber (1984) and Smidt (1985) provide evidence that locals (futures floor traders who trade exclusively for their own accounts) behave as if they are market makers. By extension, dual traders when trading for their own accounts may act primarily as market makers, as argued by Grossman (1981). Consistent with this idea, we find that, for both contracts, the *mean* realized bid-ask spread for dual traders' personal trades and locals' trades are equal.

However, for the S&P 500 futures the *median* bid-ask spread is higher than that of locals' on days when dual traders trade for customers. Since the sign and magnitudes of the median bid-ask spreads appear to be more economically meaningful than the mean spreads (for example, median spreads are always positive whereas the mean spreads are sometimes negative in our sample), we cannot rule out the possibility that the bid-ask spreads for dual traders' personal trades are "excessive" compared to those of competing market makers in the S&P 500 futures.

Next, we examine the possibility that brokers' "excess" revenues on dual trading days are legitimate trading revenues derived from customers' information, as suggested by Fishman and Longstaff (1992), Roell (1990), and Sarkar (1995). Our model predicts a negative (positive) relation between the market price impact and brokers' per contract profits from information (misallocation). We test the model's prediction by regressing dual traders' daily personal trading revenues per contract on the average daily price impact, controlling for other liquidity-related factors such as asset volatility and customer trading volume. We find that brokers' trading revenues are strongly and positively related to the market price impact for both contracts. Thus, it appears unlikely that dual traders' price advantage is attributable to information-based trading by dual traders.

As a further test, we examine whether brokers trade in the same direction as their customers, which (our model predicts) may indicate that brokers' customers are informed. We find that, for the S&P 500 futures, brokers trade in the *opposite* direction of their customers, suggesting that brokers' customers are uninformed. In the Yen futures, we find no correlation between the direction of brokers' own trades and their customers' trades.

We also examine whether dual traders receive superior prices because they try harder when trading for their own accounts. If dual brokers trade for themselves when the market is slack, then they may have more time to search for "good" prices. We find that dual traders' personal trading activities are positively correlated with market activities for the S&P 500 futures, and uncorrelated with market activities for the Yen futures. So, dual traders do not appear to engage in personal trading during times of market slack.

Finally, we investigate whether dual traders may pass on some of their trading profits to customers through lower commissions or superior execution. We do not have commissions data, but we show that, on dual trading days, customers of dual traders in the S&P 500 futures receive lower (higher) prices for buys (sells) compared to pure brokers. Since we have already shown that customers of dual traders do not have superior information, we interpret this result as evidence of superior execution skills of dual traders in the S&P 500 futures.

Related to our research are studies which examine whether dual traders provide better execution for their customers. Results from these studies are mixed. Fishman and Longstaff (1992) find that they do, but Chang and Locke (1996) and the CFTC (1989) come to the opposite conclusion.[6] These studies, however, do not directly examine the possibility that customers may receive better prices because they are better informed, and not because of dual traders' superior execution skills. Fishman and Longstaff (1992) and Chang and Locke (1996) compare trading profits of dual traders and locals to examine whether dual traders may have superior information,

---

[6] The contradictory results may be due to the markets studied since Chang and Locke (1996) study financial futures, while Fishman and Longstaff (1992) study soybean oil futures. We, too, find evidence for superior execution skills of dual traders in the S&P 500 futures market, but not in the Yen futures market.

but such comparison cannot identify the source of the information (i.e., customers or dual traders themselves). Chang and Locke (1996) correlate the net trading volumes of dual traders and customers, but they do not correlate the directions of trades, nor do they distinguish between dual traders' own customers and other customers. By directly testing for piggybacking by dual traders on their *own* customers' trades, we are able to say whether they are trading based on customers' information.

Other studies in this area focus on the liquidity effects of dual trading, although policy makers are primarily concerned about the potential for trading abuse with dual trading. The evidence on liquidity is not compelling: the effect of dual trading on liquidity can be positive, negative or neutral.[7]

Our analysis is related to recent studies of Nasdaq market makers. For example, Christie and Huang (1994) and Barclay (1995) compare spreads quoted by market makers on Nasdaq and competing exchanges. However, as Demsetz (1997) points out, conclusions drawn from such comparisons are complicated by the fact that these studies cannot distinguish between spreads set by limit order traders and spreads set by market makers when trading for their own accounts. We, on the other hand, are able to distinguish between personal trades and customer trades, and thus compare realized spreads on dual traders' own trades and those of competing market makers (locals) on the same exchange.

Another related literature deals with the relationship between market liquidity and stock returns. For example, Brennan and Subrahmanyam (1996) find a significant relation between monthly stock returns and measures of market depth obtained from intraday data while Amihud and

---

[7]Studies of dual trading featuring the bid-ask spread include the CFTC (1989), Walsh and Dinehart (1991), Fishman and Longstaff (1992), Smith and Whaley (1994), and Chang and Locke (1996).

Mendelson (1986) find evidence that asset returns include a significant premium for the quoted spread. In contrast, we find that the price paid by futures customers includes a premium for the realized spread of brokers, which in turn is related to brokers' liquidity provision.

The remainder of the paper is organized as follows: Section 1 illustrates the theoretical possibility of misallocation, derives the determinants of dual traders' legitimate and misallocation profits, and shows that, with a competitive market for brokerage services, some or all of brokers' profits may be handed back to customers. Section 2 tests for price differences between brokers' own trades and their customers' trades. Sections 3, 4 and 5 consider alternative explanations for the price differences: liquidity supply, information-based trading by brokers, and greater effort by brokers for their personal trading. In section 6, we examine whether brokers' profits are passed on to customers. Section 7 concludes.

1. Misallocation of Trades by Brokers: A Theoretical Discussion

In this section, we establish the theoretical possibility that dual traders may misallocate customer trades, by reserving better trade prices for themselves. We derive the determinants of brokers' legitimate profits from dual trading, and their profits from misallocation. Finally, we show that, if the brokerage services market is competitive, dual trading brokers may pass on some of their trading profits to customers by providing them with better prices relative to pure brokers.

We consider a two period asset market structured along the lines of Kyle (1985). There is a single risky asset with random value v, drawn from a normal distribution with mean 0 and variance Σ_v. There is an informed trader who observes v and submits market orders. Uninformed noise traders place market orders u_1 and u_2, in periods one and two, respectively, where u_t, for $t = 1,2$, is also normal with mean 0 and variance Σ_u. All random variables are independent of one another.

The informed customer and uninformed noise traders must trade through a broker who submits customer orders to the market maker. By observing the informed order, the broker can infer v. By observing the orders of noise traders, he is aware of the size of uninformed trades. Thus, the broker has an incentive to trade based on customer orders. The broker is not allowed to trade ahead of (i.e., front run) customers. Initially, the broker is also not allowed to switch customer trades.

In period one, the broker receives market orders from the informed trader and noise traders, which he then submits to the market maker. In period two, the broker trades for himself, along with period two noise traders. Each period, a market marker sets a price to earn zero expected profits, conditional on the order flow history.

The model is solved by backward induction. Given the period one choice x by the informed trader and u_1 by noise traders, the broker chooses personal trading quantity z in period two to maximize conditional expected profits $E[(v-p_2)z|x,u_1,p_1]$, where the conditioning is based on the broker's observation of informed and uninformed orders received, and the period one price. The period two price is $p_2 = \lambda_2 y_2+\mu_2 y_1$ where y_t is the period t net order flow, and $y_2 = z + u_2$.

The broker's period two trading rule $z(x,u_1)$ only depends on x and u_1, and not on the period one price p_1, since the latter does not contain any information additional to x and u_1. In period one, the informed trader observes v and chooses x, assuming (correctly) that his order will be executed in the first period. Accordingly, the informed trader chooses x to maximize conditional expected profits $E[(v-p_1)x|v]$,where the period one price is $p_1 = \lambda_1 y_1$, and the period one net order flow is $y_1 = x+u_1$. Proposition 1 below solves for the unique linear equilibrium in this market.

Proposition 1: In the unique linear equilibrium, the informed trader trades $x = Av$ in period one, and the price is $p_1 = \lambda_1 y_1$. In period two, the broker trades $z = B_1 x + B_2 u_1$, where the price

is $p_2 = \lambda_2 y_2 + \mu_2 y_1$, and:

$$A = \frac{\sqrt{\Sigma_u}}{\sqrt{\Sigma_v}} \tag{1}$$

$$\lambda_1 = \frac{\sqrt{\Sigma_v}}{2\sqrt{\Sigma_u}} = \mu_2 \tag{2}$$

$$B_1 = \frac{1}{\sqrt{2}} \tag{3}$$

$$B_2 = -\frac{1}{\sqrt{2}} \tag{4}$$

$$\lambda_2 = \frac{\sqrt{\Sigma_v}}{\sqrt{\Sigma_u}} \frac{1}{2\sqrt{2}} \tag{5}$$

Proof: See appendix.

The period one solution is identical to Kyle's (1985) single period equilibrium. Thus, the informed trade is unaffected by brokers' trading in period two since it is executed only in period one. In period two, the dual trader piggybacks on period one informed trades (B_1>0) and offsets period one noise trades ($B_2<0$).

A. Misallocation by Dual Traders

To illustrate the possibility of misallocation, suppose the period one and period two trades occur close together in time and the broker does not report trades to customers before observing the period two price. It is clear from Proposition 1 that trades executed by the dual trader for customers and his own account can occur at different prices (i.e., $p_1 \neq p_2$), even when these trades occur close together in time. From (2) and (5):

$$p_2 - p_1 = \lambda_2 y_2 = \frac{\sqrt{\Sigma_v}}{\sqrt{\Sigma_u}} \frac{1}{2\sqrt{2}} y_2 \tag{6}$$

The dual trader can profit by claiming the trade which receives the better price as his own. For example, consider the case where all customers and the dual trader purchase the asset and so $p_2 > p_1$. Then, the dual trader has an incentive to claim a customer's purchase at p_1 as his own, and allocate his own purchase at p_2 to the customer.[8]

From (6), the incentive to misallocate is higher, the greater is the price difference (p_2-p_1). Below we describe two scenarios likely to cause a large price change from one trade to another.

Scenario 1 (Market volatility). From (6), the price change (p_2 - p_1**)** is decreasing in the noise volatility Σ_u and increasing in the asset volatility Σ_v. Thus, in times of high volatility, or when the size of noise trades is low, misallocation is more likely.

Scenario 2 (Market uncertainty). In the futures pit, it is never known for sure whether a particular floor broker is a dual trader or a pure broker.[9] This uncertainty on the part of the market maker may increase price uncertainty and provide dual traders increased opportunity to misallocate customer trades. To illustrate this argument, suppose the market maker does not know for sure whether the period two trade is by an informed customer or a dual trader. Let $d(y_2)$ be the market maker's probability that the period two trade is by a dual trader, conditional on observing the net order flow

---

[8]If the informed trader has a prior probability assessment regarding the likelihood of misallocation, he might take this into account when formulating his trading strategy. As long as misallocation does not occur with probability one, however, the logic of our simple model should remain valid in a more complex setup where the informed trader anticipates the possiblity of the broker's misallocation.

[9]Floor traders try to infer whether another floor trader trades for a customer or his own account by observing the latter's clearing members. If a single clearing member receives most of the trades, then it is likely that the floor trader trades for his own account. If several different clearing members receive trades, then the floor trader is likely to be an independent broker.

y_2.[10] Let [1-$d(y_2)$] be the market maker's belief that the period two order flow is $y_2 = x_{2m} + u_2$, where x_{2m} is an order from another informed trader, different from the dual trader and from the period one informed trader, and who has also observed v.

Given this belief, and after observing y_2, the market maker sets a price $p_{2m} = p_1 + \lambda_{2m} y_2$ with probability [1-$d(y_2)$]. We can easily calculate p_{2m} since this price is equivalent to the Kyle (1985) single period price. Thus, with probability [1-$d(y_2)$], the price change from period one to period two (details in appendix) is:

$$p_{2m} - p_1 = \lambda_{2m} y_2 = \lambda_2 y_2 \sqrt{2} > \lambda_2 y_2 \qquad (7)$$

With probablity $d(y_2)$, the market makers sets a price p_2 . From Proposition 1, $p_2 = p_1 + \lambda_2 y_2$, where λ_2 is given by (5). Thus, the expected price change in period two is:

$$y_2[(1-d(y_2))\lambda_{2m} + d(y_2)\lambda_2] > y_2\lambda_2 \qquad (8)$$

The second inequality follows if $d(y_2)$>0 because, from (7), $\lambda_{2m} > \lambda_2$. Thus, uncertainty on the part of the market maker as to the likelihood of dual trading can induce large price changes, and create a positive incentive for misallocation.

B. Brokers' Legitimate Trading Profits and Profits from Misallocation.

Dual traders can make profits legitimately through piggybacking on customer trades, as shown in Proposition 1. To distinguish between such legitimate profits and profits from misallocation, we analyze the determinants of the dual trader's profits from these two sources.

Proposition 2. 1) Brokers' realized trading profits per contract are decreasing in the market

---

[10] An example of such an updating rule can be found in the dual trading model of Fishman and Longstaff (1992).

price impact.

2) Brokers' realized profits per contract from misallocation are increasing in the market price impact.

Proof: Let W denote the dual trader's ***realized*** piggybacking profits *per contract.* Let D denote the dual trader's ***realized*** misallocation profits ***per contract****.*

$$\begin{aligned} W &= (v-p_2) = (v - \lambda_2 y_2 - \lambda_1 y_1) \\ D &= p_2 - p_1 = \lambda_2 y_2 \end{aligned} \tag{9}$$

Since λ_t, $t = 1,2$, is the price impact of a unit of order flow, W is *decreasing* in the period one price impact λ_1 and the period two market price impact λ_2, while D is *increasing* in the period two market price impact. The result is intuitive: when piggybacking, the dual trader is like an informed trader and profits when prices do not respond much to their trades (market depth is high). When misallocating customer trades, his profits are potentially higher when successive price changes are higher (market depth is low).

C. Misallocation and Customer Welfare

Since trading is a zero-sum game (the market maker makes zero expected profits on average), if dual trader's profits from misallocation exceed their legitimate profits, the excess profits are at the expense of customers. However, customers may not be hurt if the profits are returned to them in the form of lower commissions, or price discounts.

Proposition 3. If the market for brokerage services is competitive, then customers of dual traders receive a larger price discount and/or lower commissions relative to what they would receive from a pure broker.

Proof: Suppose the dual trader charges a fee of $\$c$ per customer trade, and this is independent of the order size. Following Fishman and Longstaff (1992), we assume that the broker faces a variable cost k_1 per customer trade, with $k_1>0$. We also assume that the brokerage business is competitive and so the broker chooses c to break even on each trade.

We analyze the determination of c from the informed trader's point of view. In period zero, the broker chooses the fee c to charge each customer. Then, the informed trader observes v and chooses x to maximize conditional expected *net* profits $E[(v-p_1)x|v] - c$. To avoid technical problems related to non-trading, we assume that c is small enough that equilibrium net profits are always positive. The precise condition is that c satisfies:

$$2c < \sqrt{\Sigma_u \Sigma_v} \tag{10}$$

Let M be the broker's profits from misallocation, per *customer* trade. The broker's zero profits condition implies that, for each customer trade:

$$M + c = k_1 \tag{11}$$

Let c_n be the fee charged by a pure execution broker (i.e., a broker who does not trade for his own account). Analogous to (11), we have:

$$c_n = k_1 \tag{12}$$

From (11) and (12), if $M>0$, then $c<c_n$. This result was previously shown in Fishman and Longstaff (1992) and Sarkar (1995).

Alternatively, the dual trading broker may provide a price discount to customers. Let P_d be the trade price charged to the customer by the dual trader, and let α represent the fraction of profits M that the dual trader wants to pass on to the customer in the form of a price discount. Since the dual trader must pay P_d to the market maker, we can rewrite (11) as follows:

$$\left[\left(P_d - \alpha M\right) - P_d\right] + M + (\alpha M + c) \;=\; k_1 \qquad \textbf{(13)}$$

In (13), the broker makes up the price discount by charging higher commissions ($\alpha M+c$).

Let P_b be the price charged and B be the price discount given by the pure execution broker. Analogous to (13), we have:

$$(P_b - B - P_b) + (B + c_n) = k_1 \qquad (14)$$

Equating (13) and (14):

$$\alpha M - B = M + (\alpha M + c) - (c_n + B) \qquad (15)$$

Assume that the dual trader charges the same "effective" commission as the pure broker: $\alpha M + c = B + c_n$. Then, from (15), $\alpha M - B = M > 0$: the dual trading broker provides a price discount larger than the pure broker by an amount equal to the misallocation profits per customer trade.

In the remainder of this paper, we study empirically whether dual traders receive more favorable prices than their customers, whether this is due to misallocation, and whether dual traders compensate their customers fully or partially by sharing any profits from misallocating trades.

2. An Empirical Analysis of Brokers' Misallocation

We use the Chicago Mercantile Exchange's Computerized Trade Reconstruction (CTR) data for the S&P 500 index futures and the Japanese yen futures during fifteen randomly selected days for the period May 1 to June 13, 1987.[11] The data provide for each trade, the customer type, the trade type, the number of contracts traded, the trade price, and a buy-sell indicator with all variables dated

[11]We choose 1987 because we wish to control for the effect on dual traders' behavior of Chicago Mercantile Exchange regulations, such as the Top Step rule of June 21, 1987 (reserving the use of the top step of the pit to pure brokers in the S&P 500 futures market) and the banning of dual trading in "mature liquid" contracts in 1991 (which affected the Japanese yen futures, among others).

at thirty minute brackets or intervals. The customer type is classified by four indicators. We focus on trades indicated by Customer Type Indicator 1 (trades executed for floor traders' own accounts) and Customer Type Indicator 4 (trades for outside customers), which are relevant for dual trading.[12] The majority of trades fall under these two categories.

The S&P 500 sample contains 412,441 trades and 794 traders active during the fifteen sample days, with a daily average volume of more than 94,000 contracts. Our Japanese yen sample contains 56,006 trades and 251 traders, with a daily average trading volume of almost 20,000 contracts.

A. The Dual and Nondual Trading Samples

The following method is used to construct the dual trading and nondual trading samples. Let x_{it} = (personal trading volume)/(total trading volume) for trader *i* on day *t*. Depending on the value of x_{it}, we define day *t* as a dual day, a local day, or a broker day for trader *i* in the following way. Day *t* is a dual day for floor trader *i* if $0.02 \leq x_{it} \leq 0.98$,[13] a local day if $0.98 < x_{it} \leq 1$, and a broker day if $0 \leq x_{it} < 0.02$. We define a dual trader as a floor trader with at least one dual day in the sample period. Thus, the dual trader sample consists of the dual days, local days, and broker days of dual traders. A local (broker) is a floor trader who trades exclusively for his own (customer's) account for every day he is active. Thus, the local (broker) sample consists exclusively of local (broker) days

---

[12]The other indicators are Customer Type Indicator 2 (trades executed for a clearing member's house account) and Customer Type Indicator 3 (trades for another member present on the exchange floor).

[13]The 2 percent filter is used to allow for the possibility of error trading. As Chang, Locke, and Mann (1994) state, "when a broker makes a mistake in executing a customer order, the trade is placed into an error account as a trade for the broker’s personal account. The broker may then offset the error with a trade for the error account. A value of 2 percent for this error trading seems reasonable from conversations with Commodity Futures Trading Commission and exchange staff."

of locals (brokers).

Alternatively, one may categorize a floor trader *i* on a daily basis according to the value of x_{it}. This alternative definition focuses on the activity of a particular trader since, by this definition, a floor trader may (for example) be a dual trader one day, and a local on a different day. By our definition, in contrast, a floor trader is either a dual trader, or a local, but never both. Our definition separates the functions of a dual trader (i.e., brokering, personal trading, and dual trading) and thus provides a way to test whether the behavior pattern of a dual trader is associated specifically with dual trading. For example, if dual trader *i* is consistently misallocating customer trades to his own account, we can check whether the bid-ask spread on his personal trades is "excessive" only on his dual trading days.[14]

B. Activity Level of Dual Traders

Table 2 provides information on the activities of dual and nondual floor traders. Of all floor traders, dual traders are the most active. For the S&P 500 futures, 212 out of 794 floor traders are dual traders. Of the number of active floor traders per day,[15] however, 121 of 357 active floor traders on a given day are dual traders. Similarly, while the average trader is active for almost seven

[14]We pay a small price for the advantages of our way of defining floor traders. Specifically, we are forced to omit a few floor traders who trade as locals on some days and as pure brokers on other days since they do not fit into any of our categories. There were thirteen such traders in the S&P 500 futures sample and six traders in the Japanese yen futures sample, and they accounted for a minor proportion of trading activity.

[15]The number of active floor traders is calculated by dividing the number of trader days by 15, the number of days in sample for each type of trader.

days,[16] the average dual trader is active for almost nine days. For the Japanese yen futures, 52 of 251 floor traders are dual traders. But, 35 of 93 active traders per day are dual traders, and the average dual trader has 10 active days, compared to 5.5 days for the average trader.

Table 3 provides information on trading frequency and volume during dual and nondual trading days of floor traders. The main finding here is that trading frequency is three-to-four times higher and average volume is about two times higher on dual trading days, compared to nondual trading days. For example, in the S&P 500 futures, the number of trades per trader day is 153 on dual trading days, compared to 56 on broker days and 54 on local days. Volume per trader day is 554 on dual trading days, compared to 290 on broker days and 157 on local days.

The high level of trading activity by dual traders suggests that there were ample opportunities for dual traders to misallocate customer trades. Equally, the data may indicate that dual traders were active liquidity providers to the market.

C. Misallocation by Dual Traders

To test whether dual traders receive more favorable prices than their customers, we compute for each trading bracket, and for buys and sales separately, the average volume weighted price of dual traders' customer trades and personal trades on dual trading days. For trading bracket *j*, let P_{j4B} and P_{j4S} be the prices for purchases and sales, respectively, executed by dual traders for their customers. Similarly, P_{j1B} and P_{j1S} are the prices for purchases and sales by dual traders for their own accounts in bracket *j*. The null hypothesis is $(P_{1B} - P_{4B}) = 0$ and $(P_{1S} - P_{4S}) = 0$, where $(P_{1B} - P_{4B})$

---

[16] This number is calculated by dividing the number of trader days by the number of traders. These numbers understate the activity level of the median trader because many traders were active for just one or two days during our sample period.

is the mean value of (P_{j1B} -P_{j4B}), and (P_{1S} -P_{4S}) is the mean value of (P_{j1S} -P_{j4S}). The test statistic is the paired *t*, found by calculating the mean and standard deviations of the *difference* series (P_{j1B} -P_{j4B}) and (P_{j1S} -P_{j4S}). Note that our unit of observation is a trading bracket, giving us 210 observations for the S&P 500 contract and 154 observations for the Yen contract.

Table 4 provides evidence consistent with misallocation of customer trades by dual traders. For both contracts, dual traders on average receive more favorable prices when trading for their own accounts than when trading for customers. They buy at a lower price and sell at a higher price than their customers, and these differences are significant. For example, in the S&P 500 futures, dual traders on average sell a contract for their own account at an average price of 291.0927, but sell for their customers at an average price of 290.9985. The difference of 0.0942, or a cash equivalent of $47.10 per contract,[17] is significant at the 1 percent level. For the Yen futures, the price differences are lower in magnitude, but still significant at the 2.5 percent level.

3. Are Price Differences Due to Brokers' Compensation for Supplying Liquidity?

There are three alternative explanations for the price differences found earlier. First, dual traders when trading for their own accounts act like market makers, quoting bid and ask prices, and interacting with the public order flow. Thus, the price difference may measure the compensation to dual traders for providing market making services. Second, dual traders, by virtue of observing customers' order flow, may have better knowledge of supply and demand conditions in the market.

---

[17]To obtain the cash equivalent value in dollars for the S&P 500 futures, we multiply the price, which is quoted in dollars per index point, by 500. For the Yen futures, which is quoted in dollars per 100 yens, we multiply the price by 125,000 yens.

This allows them to trade at opportune times. Finally, dual traders may try harder to search for a better price when trading for themselves.[18] In this section, we examine the first alternative explanation for the price difference.

To test whether dual traders are compensated for market making skills, we compare the average bid-ask spread for dual traders' own trades with locals' trades. Locals' trading strategies closely resemble those of market makers. For example, Silber (1984) and Smidt (1985) argue that locals provide "immediacy", or immediate liquidity, by trading frequently and in small amounts. Thus, if dual brokers trade mainly as market makers, the average bid-ask spread on their trades should, on average, be similar to those on locals' trades. On the other hand, if dual traders are misallocating customer trades, the average bid-ask spread on their personal trades should be "excessive"---i.e., higher than the average bid-ask spread on locals' trades.

We proceed as follows. For each trading bracket, and for buys and sales separately, we calculate the average volume weighted price of locals' trades and dual traders' personal trades. For bracket *j*, P_{j1B} and P_{j1S} are the prices for purchases and sales, respectively, by dual traders for their own accounts. Similarly, P_{jLB} and P_{jLS} are the prices for purchases and sales, respectively, executed by locals in bracket *j*. The null hypothesis is $(P_{1S} - P_{1B}) - (P_{LS} - P_{LB}) = 0$, where $(P_{1S} - P_{1B})$ is the mean value of $(P_{j1S} - P_{j1B})$, and $(P_{LS} - P_{LB})$ is the mean value of $(P_{jLS} - P_{jLB})$. The test statistic is the paired *t*, calculated from the mean and standard deviation of the spread *differences* $[(P_{j1S} - P_{j1B}) - (P_{jLS} - P_{jLB})]$. The comparison is carried out for dual days of dual traders (i.e., days when they trade both for

[18] We are grateful to James Moser for this suggestion.

customers and for their own accounts).[19]

Table 5 shows that, for both contracts, there is no statistically significant difference between the mean bid-ask spreads of dual traders and locals. For example, in the S&P 500 futures, the mean bid-ask spread for dual traders is 0.0852 (or, $42.60) per contract compared to 0.0888 (or, $44.40) per contract for locals, but this difference is not statistically significant. This is consistent with the null hypothesis that the price difference is compensation for liquidity supplied by dual traders.

However, the sign and magnitude of the mean spreads are not always economically meaningful. For example, the bid-ask spread has a negative value for the Yen futures, and the dollar value of the bid-ask spread is approximately twice the exchange-mandated minimum tick, or price change, for both contracts.[20] Therefore, we also compare the *median* revenues per contract for personal trades of locals and dual traders, using the Wilcoxon difference in medians test. Per contract revenues are the realized differences between the average sell and buy prices received by floor traders, and thus another measure of realized bid-ask spreads. They are calculated on a daily basis by subtracting the value of purchases from the value of sales for each trader, with imbalances valued at the daily settlement prices (marked-to-market) of the Chicago Mercantile Exchange. Aggregate daily revenues are divided by the number of round-trip transactions for each floor trader to obtain daily revenues per contract. As before, the comparison is carried out for both local and dual days of dual traders.

---

[19] We also tested for differences in spreads for local days--i.e, days when dual traders traded exclusively for themselves. Since the results do not differ, we report results for dual days only.

[20] For the S&P 500, the minimum tick is $25 and, for the Yen, the minimum tick is $12.50. On the basis of prior research and market knowledge, we expect the bid-ask spread per contract to be, approximately, of the same order of magnitude as the minimum price change for the contract.

Table 6 reports the results on personal trading revenues (in dollars) of dual traders and locals. Consistent with Table 5, mean revenues are either negative or have economically unrealistic magnitudes for both contracts. However, median revenues are always positive and have economically sensible values. In addition, the distribution of revenues exhibits negative and positive skewness (not reported), varying between -0.48 and 0.5. For the S&P 500 futures, dual traders have significantly higher median personal trading revenues per contract on their dual days compared to locals. On local days, however, personal trading revenues per contract of dual traders and locals are not significantly different. For the Japanese yen futures, there is no significant difference between dual traders' and locals' median revenues per contract on either dual days or local days.

These results show that, for the Yen futures, the bid-ask spread on dual traders' personal trades is not excessive compared to that of competing market makers. However, for the S&P 500 futures, there is some evidence that the median spread on dual traders' personal trades is too high relative to competing market makers. In the next section, we examine whether the additional spread enjoyed by dual traders is due to superior information obtained from their customers.

4. Are Price Differences due to Brokers' Superior Information?

In this section, we test the validity of the second alternative explanation for brokers' price advantage---namely, whether dual traders, by virtue of observing customers' order flow, benefit from their customers' superior information. This may explain the results of Table 6 for the S&P 500 futures, showing the profitability of dual traders' personal trades on their dual trading days.

Dual traders may legitimately profit from their customers' information by piggybacking on customer trades. Proposition 2 suggests a way to distinguish between dual traders' legitimate profits and profits from misallocation. Specifically, piggybacking profits *per contract* should be negatively related to the market price impact, whereas misallocation profits *per contract* should be positively related to the market price impact.

To test this hypothesis, we estimate the following regression using the Ordinary Least Squares (OLS) method.

$$\begin{aligned} P_t &= a_0 + a_1 LV_t + a_2 VOL_t + a_3 M_t + a_4 PIMP_t \\ &\quad + b_0 D_t + b_1 D_t LV_t + b_2 D_t VOL_t + b_3 D_t M_t + b_4 D_t PIMP_t + e_t \end{aligned} \tag{16}$$

where, for day t, P_t is dual traders' personal trading revenues (in dollars) per contract on their dual trading days, LV_t is log of customer trading volume, VOL_t is a proxy for volatility, M_t is the number of market makers, $PIMP_t$ is a proxy for the market price impact (in dollars), and the dummy variable D_t is equal to 1 for the S&P 500 futures and 0 otherwise. Volatility is measured by the standard deviation of prices for purchases *only* (to control for the bid-ask bounce). The number of market makers is approximated by the number of floor traders trading for their own account on each day.

$PIMP_t$ is calculated as follows. For each bracket, we divide the price change (the difference between the prices of the first and last trades) by the signed customer volume to obtain the price impact for that bracket, and then average across all brackets for the day to obtain the average daily market price impact. To be economically meaningful, $PIMP_t$ should be positive for every t, which is the case in our sample.[21] Note that, in contrast to Table 6, revenues are calculated on a *sample* day basis, rather on a *trader* day basis. In other words, to obtain P_t, we calculate revenues for day

---

[21]This definition of market price impact is consistent with Kyle (1985), where it is denoted λ. Kyle (1985) shows that $\lambda>0$ in equilibrium.

t for each dual trader as before and then average over all dual traders active on day *t*. This is necessary since our right-hand side variables are defined on a *sample* day basis.

The dummy variable D_t controls for contract-specific effects. The coefficient estimates for the Yen futures are given by $\hat{a}_i$, i = 0,1,2,3,4, and for the S&P 500 futures are given by $(\hat{a}_i+\hat{b}_i)$. We use the F statistic to test the joint hypotheses $\hat{b}_0 = \hat{b}_1 = \hat{b}_2 = \hat{b}_3 = \hat{b}_4 = 0$.

The key parameters are a_4 and b_4. Whereas negative values of $\hat{a}_4$ and $(\hat{a}_4+\hat{b}_4)$ indicate that brokers' profits may be due to information, positive values of $\hat{a}_4$ and $(\hat{a}_4+\hat{b}_4)$ are consistent with misallocation as a source of brokers' profits. $\hat{a}_1$ and $(\hat{a}_1+\hat{b}_1)$ can be positive or negative. On days with high customer trading volume, brokers may be too busy executing customer trades and earning commissions to trade profitably on their own accounts, and so $\hat{a}_1<0$ and $(\hat{a}_1+\hat{b}_1)< 0$. Conversely, days with frequent trading by customers may provide extra opportunities for piggybacking or misallocating trades, and so $\hat{a}_1>0$ and $(\hat{a}_1+\hat{b}_1)> 0$. $\hat{a}_2 > 0$ and $(\hat{a}_2+\hat{b}_2) > 0$ if dual traders anticipate volatility and thus widen the spread to protect themselves. $\hat{a}_2 < 0$ and $(\hat{a}_2+\hat{b}_2) < 0$ if dual traders are surprised by volatility. An increase in the number of market makers should reduce trading profits, implying $\hat{a}_3 < 0$ and $(\hat{a}_3+\hat{b}_3)< 0$.

Table 7 presents the results. $\hat{a}_4$ and $\hat{b}_4$ are both positive and significant, consistent with the hypothesis that, for both contracts, brokers' profits are from misallocating trades, and not from superior information. If buying (selling) one contract increases (decreases) the price by one dollar, then revenues per contract increases 5 cents for the Yen futures, and 17 cents for the S&P 500 futures. $\hat{b}_3$ is negative and significant, and $(\hat{a}_3 + \hat{b}_3) < 0$, indicating that an increase in the number of market makers decreases brokers' revenues for the S&P 500 contract. $\hat{b}_1$ is positive and significant, and $(\hat{a}_1 + \hat{b}_1) > 0$, indicating that commission income and trading profits may be complements for the S&P 500. The coefficient of volatility is not significant, consistent with the results of Locke and Sarkar (1996).

To further check the robustness of the results of Table 7, we test for piggybacking behavior by dual traders. Proposition 1 predicts that, if a dual trader's customers are *informed*, he will trade in the *same* direction as his customers, whereas if they are *uninformed*, he will trade in the *opposite* direction to his customers.

We assign the number +1 to a trading bracket if dual trader i is a net buyer for his personal account in that bracket, and the number -1 if he is a net seller for his personal account. We do a similar assignation to trades executed by dual trader i for his ***own*** customers. For dual trader i, R_{io} is the rank correlation between these two series of numbers. We also check whether those who are ***not*** dual trader i's customers are net buyers or sellers in trading bracket j and assign numbers +1or -1, accordingly. For dual trader i, R_{in} is the rank correlation between the direction of his own trades and that of customers ***not*** his own. Let R_o and R_n be the mean values of R_{io} and R_{in}, respectively.

If dual traders' customers are informed, then $R_o > 0$. If R_n is also positive, we further require that $(R_o - R_n) > 0$. If dual traders' customers are not informed, then $R_o<0$. The null hypothesis is $(R_o - R_n) = 0$, where $(R_o - R_n)$ is the mean value of $(R_{io} - R_{in})$.

Table 8 shows that, for the S&P 500 futures, $R_o<0$. Although R_n is also negative, $(R_o - R_n) < 0$, and this is statistically significant at the one percent level. This result indicates that dual traders' customers in the S&P 500 futures may be uninformed. For the Yen futures, $R_o > 0$ and $R_n < 0$, but the difference $(R_o - R_n)$ is not statistically different from zero. These results are consistent with those in Table 7, indicating either that dual traders' customers are not informed or, if they are, dual traders do not take advantage of that information.

5. Do Brokers Make Additional Efforts For Their Own Trades?

In this section, we examine whether brokers' price advantage is due to greater effort by dual traders when trading for themselves. Grossman (1989) argues that dual traders' personal and customer trades are substitutes. When the market is active, dual traders engage in brokerage. When the market is slack, they trade for themselves. Thus, during a market slack, dual traders may have more time to search for better prices when making their own trades.

The above argument implies that there may be a negative relation between dual traders' own activities and those of the market. The results of Table 7 do not support this contention, since dual traders' revenues and customer trading volume are positively related for the S&P 500 futures ($(\hat{a}_1 + \hat{b}_1) > 0$) and unrelated for the Yen futures. As a further test, we compute, for each dual trader *i* on his dual trading day, and for each trading bracket, the correlation between the number of trades for his own accounts and the number of trades for *all* customers (both his own customers and those of other brokers). Let R_{im} be the correlation for dual trader *i*, averaged over all brackets. Let R_m be the mean correlation for all dual traders. Under the null hypothesis, $R_m = 0$. If dual traders' personal and customer trading activities are substitutes, then $R_m<0$.

Table 9 shows the results. For the S&P 500 futures, R_m is positive, but not significant. For the Yen futures, $R_m<0$ but not significantly different from zero. These results provide little evidence that dual traders expend greater efforts when making their personal trades, relative to when they execute trades for customers.

6. Do Brokers Share Profits With Customers?

The results of Table 6 show that brokers' trading is profitable. Proposition 3 suggests the possibility that dual traders may share some of the profits with customers by providing superior execution. We compute for each trading bracket, and for buys and sales separately, the average volume weighted price of the customer trades of dual traders and pure brokers. If dual traders provide superior execution for customers compared to pure brokers, they should on average buy (sell) for customers at lower (higher) prices relative to pure brokers. Further, if dual traders' customers receive better prices, this cannot be due to their superior information, since evidence from Tables 7 and 8 have already ruled out this possibility.

Let P_{BB} and P_{BS} be the mean prices for purchases and sales, respectively, executed by pure brokers for their customers. Similarly, P_{4B} and P_{4S} are the mean prices for purchases and sales, respectively, by dual traders for their customers. The null hypothesis is $P_{4B} - P_{BB} = 0$ and $P_{4S} - P_{BS} = 0$. Table 10 reports the results on execution skills of dual traders and pure brokers. For the S&P 500 futures, dual traders' customers buy at lower prices and sell at higher prices compared to customers of pure brokers. For example, customers of pure brokers pay 291.1438 to buy one S&P 500 futures contract, whereas customers of dual traders pay 291.115 for the same purchase. The difference of 0.0288, or a cash equivalent value of $14.40 per contract, is significant at the 2.5 percent level. For the Japanese yen futures, the difference in prices paid by the two sets of customers are the same is not significant.

Combining the results of Tables 4 and 10, dual traders appear to share some profits with customers, at least in the S&P 500 futures. For example, customers of dual traders pay $53.75 more to buy one S&P 500 futures contract, compared to dual traders' own trades, but $14.40 less than if they had used a pure broker.

7. Conclusion

In the context of futures markets, we study whether brokers allocate more favorable trades to their own accounts, and less favorable trades to their customers. We find that, within a thirty minute trading bracket, brokers on average buy at a lower price and sell at a higher price for their own accounts relative to their customers. We show evidence that this price advantage may be brokers' compensation for providing liquidity when trading for their own accounts, but no evidence that they are from superior information, or from extra effort when trading for themselves. We find that brokers who trade for themselves also provide superior execution to customers, relative to pure brokers, suggesting that brokers may share trading profits (from whatever source) with customers.

References

Amihud, Yakov and Haim Mendelson, 1986. "Asset Pricing and the Bid-Ask Spread." *Journal of Financial Economics* 17, 223-249.

Barclay, M.J., 1995. "Bid-ask Spreads and the Avoidance of Odd-Eighth Quotes on Nasdaq: An Examination of Exchange Listings." *Journal of Financial Economics* 45, 35-60.

Brennan, Michael J. and Avanidhar Subrahmanyam, 1996. "Market Microstructure and the Asset Pricing: On the Compensation for Illiquidity in Stock Returns." *Journal of Financial Economics* 41, 441-464.

Christie, W.G. and R. Huang, 1994. "Market Structure and Liquidity: A Transactions Data Study of Exchange Listings." *Journal of Financial Intermediation*, 3, 300-326.

Chang, Eric C., and Peter R. Locke. 1996. "The Performance and Market Impact of Dual Trading: CME Rule 552." *Journal of Financial Intermediation*, 5, 23-48.

Chang, Eric C., Peter R. Locke, and Steven C. Mann. 1994. "The Effect of CME Rule 552 on Dual Traders." *The Journal of Futures Markets* 14, no. 4: 493-510.

Commodity Futures Trading Commission (CFTC). 1989. "Economic Analysis of Dual Trading on

Commodity Exchange." Division of Economic Analysis, Washington, D.C.

Demsetz, Harold. "Limit Orders and the Alleged Nasdaq Collusion." *Journal of Financial Economics* 45, 91-95.

Fishman, Michael J., and Francis A. Longstaff. 1992. "Dual Trading in Futures Markets." *The Journal of Finance* 47, no. 2: 643-71.

Grossman, Sanford J. 1989. "An Economic Analysis of Dual Trading." Rodney L. White Center for Financial Research Paper no. 33-89. The Wharton School, University of Pennsylvania.

Holden, C.W. and A. Subrahmanyam. 1992. "Long-lived private information and imperfect competition." *Journal of Finance* 47, 247-270.

Kuserk, Gregory J., and Peter R. Locke. 1993. "Scalper Behavior in Futures Markets: An Empirical Examination." *The Journal of Futures Markets* 13: 409-31.

Locke, Peter R. and Asani Sarkar. 1996. "Volatility and Liquidity in Futures Markets." Research paper #9612, the Federal Reserve Bank of New York.

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

Manaster, Steven, and Steven C. Mann. 1996. "Life in the Pits: Competitive Marketmaking and Inventory Control." *Review of Financial Studies*, 9, 3, 953-975.

Roell, Ailsa. 1990. "Dual Capacity Trading and the Quality of the Market." *The Journal of Financial Intermediation* 1: 105-24.

Sarkar, Asani. 1995. "Dual Trading: Winners, Losers and Market Impact." *The Journal of Financial Intermediation* 4: 77-93.

Silber, William L. 1984. "Marketmaker Behavior in an Auction Market: An Analysis of Scalpers in Futures Markets." *Journal of Finance* 39: 937-53.

Smidt, Seymour. 1985. "Trading Floor Practices on Futures and Securities Exchanges: Economics, Regulation and Policy Issues." In *Futures Markets: Regulatory Issues.* American Institute for Public Policy Research, Washington, D.C.

Smith, Tom and Robert E. Whaley. 1994. "Assessing the Cost of Regulation: The Case of Dual

Trading." *Journal of Law and Economics*, 37(1), 329-36.

United States General Accounting Office. 1989a. "Chicago Futures Market: Initial Observations on Trade Practice Abuses." GAO/GGD-89-58.

United States General Accounting Office. 1989b. "Futures Markets: Strengthening Trade Practice Oversight." GAO/GGD-89-120.

Walsh, Michael J. and S. J. Dinehart. 1991. "Dual Trading and Futures Market Liquidity: An Analysis of Three Chicago Board of Trade Contract Markets." *Journal of Futures Markets*, 11(5), 519-537.

Working, Holbrook. 1967. "Tests of a Theory Concerning Floor Trading on Commodity Exchanges." *Food Research Institute Studies: Supplement*.

Table 1
Overview of Tests and Results

Table Number	Null hypothesis	Test	Result of test	
			S&P 500 futures	Japanese yen futures
I. Misallocation of trades by dual traders				
Four	Dual traders do not misallocate favorable trades to their own accounts.	Compare average price paid by dual traders on their own trades, relative to their customers' trades.	Reject	Reject
II. Alternative explanations for brokers' price advantage: liquidity supply				
Five	Price difference is compensation for liquidity supplied by dual traders.	Compare mean bid-ask spread on personal trades of dual traders and locals.	Cannot reject	Cannot reject
Six	Price difference is compensation for liquidity supplied by dual traders.	Compare median personal trading revenues per contract of dual traders and locals.	Reject	Cannot reject
III. Alternative explanations for brokers' price advantage: brokers' information advantage				
Seven	Dual traders' revenues are not from misallocation, or from customers' information.	Regress dual trading profits on the market price impact, controlling for other factors.	Reject	Reject
Eight	Dual traders do not piggyback on their informed customers' trades.	Correlate the direction of dual traders' own trades and their customers' trades.	Cannot reject	Cannot reject
IV. Alternative explanations for brokers' price advantage: increased effort by dual traders				
Nine	Dual traders do not expend more effort on their personal trades.	Correlate dual traders' personal activity and market activity.	Cannot reject	Cannot reject
V. Are brokers' profits passed on to customers?				
Ten	Dual traders do not provide superior execution for customers.	Compare customer trading costs of dual traders and pure brokers.	Reject	Cannot reject

Table 2
Summary Statistics for the Activity of Floor Traders in the S&P 500 and Japanese Yen Futures Pits

Own account refers only to floor traders who trade exclusively for their own account. Customer only denotes floor traders who trade exclusively for their customers during the sample period. Both refers to floor traders who trade both for their own account and for their customers on at least one day during the sample period. The sample period is 15 randomly selected days from May 1 to June 13, 1987, for both contracts.

	S&P 500 Futures, 1987				Japanese Yen Futures, 1987			
	Locals	Pure Brokers	Dual Traders	Total	Locals	Pure Brokers	Dual Traders	Total
Number of traders	467	115	212	794	120	79	52	251
Number of trading days	3,162	389	1,809	5,360	576	299	521	1,396
For own account only	3,162		357	3,519	576		113	689
For customer only		389	216	605		299	145	444
For both			1,236	1,236			263	263
Number of active days per trader	6.77	3.38	8.53	6.75	4.8	3.78	10.02	5.56
For own account only	6.77		1.68	4.43	4.8		2.17	2.75
For customer only		3.38	1.02	0.76		3.78	2.79	1.77
For both			5.83	1.56			5.06	1.05
Number of active traders per day	210.8	25.93	120.6	357.33	38.4	19.93	34.73	93.07
For own account only	210.8		23.8	234.6	38.4		7.53	45.93
For customer only		25.93	14.4	40.33		19.93	9.67	29.6
For both			82.4	82.4			17.53	17.53

Table 3
Trading Activity in the S&P 500 and Japanese Yen Futures Pits

Trading for own account (customers) refers to days on which a floor trader trade exclusively for its own (customers') account(s). Dual trading refers to days on which a floor trader trade both for its own account and for its customers. The sample period is 15 randomly selected days from May 1 to June 13, 1987, for both contracts.

	Trading for customers	Trading for own account	Dual trading	Total
S&P 500 Index Futures, 1987				
Number of trader days	605	3,519	1,236	5,360
Number of trades	34,082	189,368	188,991	412,441
Trades per trader day	56.33	53.81	152.91	76.95
For own account		53.81	44.11	45.5
For customers	56.33		108.79	31.45
Total volume	175,390	552,103	684,545	1,412,038
Volume per trader day	289.90	156.89	553.84	263.44
For own account		156.89	179.47	144.39
For customers	289.90		374.37	119.05
Average trade size	5.15	2.92	3.62	3.42
For own account		2.92	4.07	3.17
For customers	5.15		3.44	3.79
Japanese Yen Futures, 1987				
Number of trader days	444	689	263	1,396
Number of trades	9,875	22,194	23,937	56,006
Trades per trader day	22.24	32.21	91.02	40.12
For own account		32.21	34.1	22.32
For customers	22.24		56.92	17.8
Total volume	55,305	119,953	122,740	297,998
Volume per trader day	124.56	174.1	466.69	213.47
For own account		174.1	149.33	114.06
For customers	124.56		317.36	99.41
Average trade size	5.6	5.4	5.13	5.32
For own account		5.4	4.38	5.11
For customers	5.6		5.58	5.58

Table 4
Misallocation of Customer Trades by Dual Traders

For each trading bracket *j*, we compute the average price (weighted by the trading volume) of purchases and sales by dual traders for their own accounts (P_{j1B} and P_{j1S}, respectively) and for their customers' accounts (P_{j4B} and P_{j4S}, respectively). The null hypothesis is (P_{1B} -P_{4B}) = 0 and (P_{1S} -P_{4S})=0, where (P_{1B} -P_{4B}) is the mean value of (P_{j1B} -P_{j4B}), and (P_{1S} -P_{4S}) is the mean value of (P_{j1S} -P_{j4S}). S&P 500 prices are in dollars per index point. Yen prices are in dollars per 100 yens. Cash equivalent values, in parentheses, are in dollars. A ★★ (★) indicates estimates which are significant at the 1 (2.5) percent level. *N* is the number of trading brackets. The sample period is 15 randomly selected days from May 1 to June 13, 1987, for both contracts.

S&P 500 Futures, 1987				
	P_{j1B}	P_{j4B}	P_{j1S}	P_{j4S}
Mean	291.0075	291.115	291.0927	290.9985
Standard deviation	5.8332	5.8949	5.9034	5.8685
Minimum	277.9534	278.1255	278.002	278.0406
Maximum	302.9734	302.902	302.787	302.7248
P_{j1B}-P_{j4B}	Mean = -0.1075 (-$53.75)★★		Standard deviation = 0.3388	
P_{j1S}-P_{j4S}	Mean = 0. 0942 ($47.10)★★		Standard deviation = 0.3165	
H_o: P_{1B}-P_{4B}= 0	Paired t = - 4.6		N = 210	
P_{1S}-P_{4S}= 0	Paired t = 4.31		N = 209	
Japanese Yen Futures, 1987				
Mean	0.711293	0.711332	0.711053	0.711005
Standard deviation	0.0084519	0.0084522	0.008698	0.008696
Minimum	0.6925	0.6928	0.6928	0.692586
Maximum	0.72527	0.7253	0.72515	0.72522
P_{j1B}-P_{j4B}	Mean = -0.000039 (-$4.90)★		Standard deviation = 0.000219	
P_{j1S}-P_{j4S}	Mean = 0.000048 ($6)★		Standard deviation = 0.000297	
H_o: P_{1B}-P_{4B}= 0	Paired t = -2.188		N = 152	
P_{1S}-P_{4S}= 0	Paired t = 1.999		N = 154	

Table 5

Bid-ask Spreads on Personal Trades of Dual Traders and Locals

For each trading bracket *j*, we compute the average price (weighted by the trading volume) of purchases and sales by dual traders for their own accounts (P_{j1B} and P_{j1S}, respectively) and by locals (P_{jLB} and P_{jLS}, respectively). The null hypothesis is (P_{1S} -P_{1B}) - (P_{LS} -P_{LB})=0, where (P_{1S} -P_{1B}) is the mean value of (P_{j1S} -P_{j1B}), and (P_{LS} -P_{LB}) is the mean value of (P_{jLS} -P_{jLB}). S&P 500 prices are in dollars per index point. Yen prices are in dollars per 100 yens. Cash equivalent values, in parentheses, are in dollars. *N* is the number of trading brackets. The sample period is 15 randomly selected days from May 1 to June 13, 1987, for both contracts.

S&P 500 Futures, 1987				
	P_{j1B}	P_{jLB}	P_{j1S}	P_{jLS}
Mean	291.0075	291.0138	291.0927	291.1026
Standard deviation	5.8332	5.2649	5.9034	5.8385
Minimum	277.9534	277.5084	278.002	278.0646
Maximum	302.9734	302.5426	302.787	302.824
P_{j1S}-P_{j1B} = 0.0852 ($42.60)			P_{jLS}-P_{jLB} = 0.0888 ($44.40)	
H_o: (P_{1S}-P_{1B}) - (P_{LS}-P_{LB})=0				
Mean = -0.0036 ($1.80)		Standard deviation = 0.09458		
Paired t =-0.5503		N=209		
Japanese Yen Futures, 1987				
Mean	0.711293	0.711301	0.711053	0.71104
Standard deviation	0.0084519	0.00861	0.008698	0.0086
Minimum	0.6925	0.6924	0.6928	0.6926
Maximum	0.72527	0.7252	0.72515	0.7253
P_{j1S}-P_{j1B} = -0.00024 ($30)			P_{jLS}-P_{jLB} = -0.000261 ($32.63)	
H_o: (P_{1S}-P_{1B}) - (P_{LS}-P_{LB}) = 0				
Mean = 0.000021($2.63)		Standard deviation = 0.00058		
Paired t = 0.4464		N = 152		

Table 6

Personal Trading Revenues Per Contract of Dual Traders and Locals

Local days refer to trading revenues per contract for days on which the floor trader trades only for its own account. Dual days refer to trading revenues per contract for days on which the floor trader trades both for its own account and for its customers. Revenues are measured in dollars. The *z*-statistic tests whether the median personal trading revenues of dual traders and locals are the same. *P*-values are given in parentheses. A ★ indicates estimates which are significant at the 2.5 percent level. *N* is the number of trader days. The sample period is 15 randomly selected days from May 1 to June 13, 1987, for both contracts.

S&P 500 Index Futures, 1987			
	Local Days of Locals	Local Days of Dual Traders	Dual Days of Dual Traders
Mean revenue	29.15	19.57	38.60
Standard deviation	410.3	616.6	368.55
Minimum	-3387.5	-3565	-2615.9
First quartile	-6	-8.9	-18.65
Median	21.45	21.55	29.75
Third quartile	58.35	51.45	97.2
Maximum	3420	3712.5	2751.25
Difference in medians: duals minus locals		0.10	8.30★
Z-statistic		0.7852	3.031
(p-value)		(0.4)	(0.0024)
N	2975	316	1206
Japanese Yen Futures, 1987			
Mean revenue	22.375	-20	25
Standard deviation	455.875	589.5	286
Minimum	-1933.75	-1783.75	-1255
First quartile	-63.75	-18	-52.5
Median	11	6.125	10.875
Third quartile	136.25	190.875	57.125
Maximum	1895.25	1986.375	1460
Difference in medians: duals minus locals		-4.875	-0.125
Z-statistic		-1.137	-0.677
(p-value)		(0.3)	(0.5)
N	474	102	247

Table 7

Determinants of Dual Trading Revenues

The determinants of dual trading revenues are estimated from the following regression:

$$P_t = a_0 + a_1 LV_t + a_2 VOL_t + a_3 M_t + a_4 PIMP_t + b_0 D_t + b_1 D_t LV_t + b_2 D_t VOL_t + b_3 D_t M_t + b_4 D_t PIMP_t + e_t$$

where, for day t, P_t is dual traders' revenues per contract in dollars, LV_t is the log of customer trading volume, VOL_t is the standard deviation of buy prices for customer trades, M_t is the number of floor traders trading for their own account, $PIMP_t$ is the market price impact in dollars, and D_t=1 if the contract is the S&P 500 index futures, and 0 otherwise. The F statistic tests the null hypotheses $b_0=b_1=b_2=b_3=b_4=0$. T-statistics and p values are shown in parentheses. A ★ indicates estimates which are significant at the 5 percent level, or below. N is the number of observations. The sample period is 15 randomly selected days from May 1 to June 13, 1987 for both contracts.

a_0	a_1	a_2	a_3	a_4
698.36	-78.30	-0.12	0.17	0.05★
(1.385)	(-1.398)	(-1.12)	(0.691)	(2.712)
p=0.181	p=0.177	p=0.276	p=0.498	p=0.013
b_0	b_1	b_2	b_3	b_4
-1748.21★	177.41★	-0.21	-0.179★	0.115★
(-2.189)	(2.188)	(-0.658)	(-0.172)	(2.662)
p=0.041	p=0.041	p=0.518	p=0.485	p=0.015

N=29 Adjusted R^2=0.54

H_0: $b_0=b_1=b_2=b_3=b_4=0$ F = 3.6175 Prob > F = 0.0171

Table 8

Piggybacking by Dual Traders

For trading bracket *j*, we compute whether dual trader *i* is a net buyer or seller for his (1) personal account, and (2) ***own*** customers. We also compute whether those who are ***not*** dual trader *i*'s customers are net buyers or sellers in trading bracket *j*. In all three cases, we assign the number +1 (-1) to a trading bracket with positive net buys (sells). For dual trader *i*, R_{io} is the mean rank correlation between the direction of his trades and that of his *own* customers' trades, while R_{in} is the rank correlation between the direction of his trades and that of customers *not* his own. The null hypothesis is $(R_o - R_n) = 0$, where $(R_o - R_n)$ is the mean value of $(R_{io} - R_{in})$. A ★★ indicates estimates which are significant at the 1 percent level. *N* is the number of dual traders. The sample period is 15 randomly selected days from May 1 to June 13, 1987, for both contracts.

S&P 500 Futures, 1987		
	R_{io}	R_{in}
Mean	-0.114	-0.001
Standard deviation	0.319	0.358
Minimum	-1	-1
Maximum	+1	+1
$R_{io}-R_{in}$	Mean = -0.104★★	
	Standard deviation = 0.455	
H_o: $(R_o-R_n) = 0$	Paired t = -2.98 N = 169	
Japanese Yen Futures, 1987		
Mean	0.019	-0.0369
Standard deviation	0.465	0.411
Minimum	-1	-1
Maximum	+1	+1
$R_{io}-R_{in}$	Mean = 0.022	
	Standard deviation = 0.5122	
H_o: $(R_o-R_n) = 0$	Paired t = 0.25 N = 34	

Table 9

Dual Traders' Personal Trading Activity and Market Activity

We compute, for each dual trader *i* on his dual trading day, and each trading bracket, the correlation between the number of trades for his own accounts and the number of trades for *all* customers. R_{im} be the correlation for dual trader *i*, averaged over all brackets. R_m is the mean correlation for all dual traders. Under the null hypothesis R_m=0. *N* indicates the number of dual traders. The sample period is 15 randomly selected days from May 1 to June 13, 1987, for both contracts.

S&P 500 Futures, 1987	
	R_{im}
Mean	0.0268
Standard deviation	0.3424
Minimum	-0.9707
Maximum	0.9594
H_o: $R_m = 0$	t = 0.112 N = 202
Japanese Yen Futures, 1987	
Mean	-0.1976
Standard deviation	0.4275
Minimum	-1
Maximum	+1
H_o: $R_m = 0$	t = -0.3101 N = 45

Table 10

Execution of Customer Trades by Dual Traders and Pure Brokers

For each trading bracket *j*, we compute the average price (weighted by the trading volume) of purchases and sales by dual traders for their customers (P_{j4B} and P_{j4S}, respectively) and by pure brokers (P_{jBB} and P_{jBS}, respectively). The null hypothesis is (P_{4B} - P_{BB})=0 and (P_{4S} -P_{BS})=0, where (P_{4B} - P_{BB}) is the mean value of (P_{j4B} - P_{jBB}), and (P_{4S} -P_{BS}) is the mean value of (P_{j4S} -P_{jBS}) S&P 500 prices are in dollars per index point. Yen prices are in dollars per 100 yens. Cash equivalent values, in parentheses, are in dollars. A ★★ (★) indicates estimates which are significant at the 1 (2.5) percent level. *N* is the number of trading brackets. The sample period is 15 randomly selected days from May 1 to June 13, 1987, for both contracts.

	P_{jBB}	P_{j4B}	P_{jBS}	P_{j4S}
S&P 500 Futures, 1987				
Mean	291.1438	291.115	290.941	290.9985
Standard deviation	5.8847	5.8949	5.9032	5.8685
Minimum	278.1108	278.1255	278.0294	278.0406
Maximum	302.8013	302.902	302.5008	302.7248
P_{j4B}-P_{jBB}	Mean = -0.0288 (-$14.40)★	Standard deviation = 0.1860		
P_{j4S}-P_{jBS}	Mean = 0.0575 ($28.75)★★	Standard deviation = 0.2943		
H_o: P_{4B}-P_{BB}= 0	Paired t = -2.2438	N = 210		
P_{4S}-P_{BS}= 0	Paired t = 2.8246	N = 209		
Japanese Yen Futures, 1987				
Mean	0.711343	0.711332	0.711024	0.711005
Standard deviation	0.008418	0.0084522	0.008653	0.008696
Minimum	0.6929	0.6928	0.6927	0.6926
Maximum	0.7253	0.7253	0.7252	0.72522
P_{j4B}-P_{jBB}	Mean = -0.000011 (-$1.38)	Standard deviation = 0.000765		
P_{j4S}-P_{jBS}	Mean =0.000019 ($2.38)	Standard deviation = 0.000549		
H_o: P_{4B}-P_{BB}= 0	Paired t = -0.176	N = 152		
P_{4S}-P_{BS}= 0	Paired t = 0.430	N = 154		

Appendix

Proof of Proposition 1

In period one, the insider's problem is identical to the single period equilibrium in Kyle (1985). Thus, in equilibrium, the insider's trading intensity A and market depth λ_1 are as given in (1) and (2) of the text.

In period two, the broker's problem is to choose z to maximize conditional expected profits $E[(v-p_2)z \mid x, u_1, p_1]$, where $p_2=\mu_2 y_1 + \lambda_2 y_2$, $y_1=x+u_1$, and $y_2=z+u_2$. Using the law of iterated projections, it is easily shown that $E[(v-p_2)z \mid x, u_1, p_1] = E[(v-p_2)z \mid x, u_1]$. Thus, the first order condition for this problem is:

$$v - 2l_2 z - m_2 Av - m_2 u_1 = 0 \qquad \text{(A1)}$$

The second order condition is $\lambda_2>0$. Solving for z from (A1), after substituting for A:

$$z = \frac{v}{2l_1}\frac{(2l_1 - m_2)}{2l_2} - \frac{m_2}{2l_2}u_1 \qquad \text{(A2)}$$

Next, we solve for μ_2 and λ_2. First, we show that, if $cov(y_1,y_2)=0$, then $\lambda_1=\mu_2$.

$$\text{cov}(y_1, y_2) = \frac{1}{2l_2}\left[\frac{\Sigma_v(2l_1 - m_2)}{4l_1^2} - m_2\Sigma_u\right] \qquad \text{(A3)}$$

Substituting for λ_1 in (A3), and putting the right-hand-side (RHS) expression equal to zero, we get $\lambda_1=\mu_2$. It is also clear from (A3) that, if $\lambda_1=\mu_2$, then $cov(y_1,y_2)=0$.

$Cov(y_1,y_2)=0$ implies that $\lambda_2=cov(v,y_2)/var(y_2)$. After substituting λ_1 for μ_2, and writing out this expression:

$$\lambda_2 = \frac{\Sigma_v / 4\lambda_2}{\Sigma_v \big/ 16\lambda_2^2 + \lambda_1^2 \Sigma_u \big/ 4\lambda_2^2 + \Sigma_u} \qquad \text{(A4)}$$

Solving for λ_2 from (A4), after substituting for λ_1, we derive (5) in the text. Substituting for λ_2 and μ_2 in (A2), we get (3) and (4) in the text.

Finally, it is easy to check that, if λ_1, λ_2 and μ_2 are as given in (2) and (5), then $cov(y_1,y_2)=0$. Alternatively, instead of assuming $cov(y_1,y_2) = 0$, we can solve for μ_2 and λ_2 directly using the projection formulas $\mu_2 = \frac{\Sigma_{01}\Sigma_{22} - \Sigma_{02}\Sigma_{12}}{\Sigma_{11}\Sigma_{22} - (\Sigma_{12})^2}$ *and* $\lambda_2 = \frac{\Sigma_{02}\Sigma_{11} - \Sigma_{01}\Sigma_{12}}{\Sigma_{11}\Sigma_{22} - (\Sigma_{12})^2}$, where $\Sigma_{01}=cov(v,y_1)$, $\Sigma_{02}=cov(v,y_2)$, $\Sigma_{12}=cov(y_2,y_1)$, $\Sigma_{11}=var(y_1)$ and $\Sigma_{22}=var(y_2)$. Although the calculation is somewhat involved, the same result obtains.

Proof of Scenario 2

In period two, the second insider's problem is to choose x_{2m} to maximize conditional expected profits $E[(v-p_{2m})x_{2m} \mid v]$, where $p_{2m} = p_1 + \lambda_{2m}y_2$, $y_1=x+u_1$, and $y_2 = x_{2m}+u_2$. Thus, the first order condition for this problem is:

$$v - 2\lambda_2 x_{2m} - p_1 = 0 \qquad \text{(A5)}$$

The second order condition is $\lambda_{2m}>0$. Solving for λ_{2m} in the usual way:

$$\lambda_{2m} = \frac{\sqrt{\Sigma_v}}{2\sqrt{\Sigma_u}} \qquad \text{(A6)}$$