Who Makes Markets?
Do Dealers Provide or Take Liquidity?

Joon Chae, Albert Wang*

Sloan School of Management, MIT, Doctoral Program in Financial Economics, Cambridge, MA 02142, USA

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ABSTRACT

We explore the role of dealers to determine whether they are liquidity-providing market makers or liquidity-taking information traders. Standard models of market maker trading imply a negative contemporaneous correlation between market maker order flow and stock returns. We test this relation with a unique dataset containing trades of all dealers in a well-developed, liquid market. The correlation is strongly positive, implying that dealers take liquidity. Furthermore, dealers earn significant excess returns, in aggregate driven by information returns rather than market-making returns. Subgroup analysis reveals that dealer profits are driven by information in large-cap stocks and by market-making in small-cap stocks.

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*Corresponding author. Tel.: + 1-617-253-3637; fax: + 1-617-258-6855.
E-mail address: albert2@mit.edu (A. Wang)

1. Introduction

Dealers in financial markets are typically assumed to provide liquidity, and therefore they are often afforded special trading privileges related to order flow and trade execution. Such privileges include access to order flow and order flow information, direct connections to exchange trading mechanisms, low transaction costs, and high transaction speeds. In return, they are often assumed to perform the social and market function of supplying liquidity, for example by absorbing temporary order imbalances.

If dealers actually trade as liquidity-providing market makers, then there will be a negative contemporaneous correlation between their order flow and stock returns. This follows from both information and inventory models of market maker trades, as typified in Kyle (1985) and Grossman and Miller (1988). Kyle shows that market makers transact against net (informed plus uninformed) trade demand, with a price impact due to the potential information content embedded in net demand. Grossman and Miller show that in the absence of informational issues, market makers are willing to accommodate temporary order imbalances if they can transact at advantageous prices. In both models, when other participants buy (sell), they push the price up (down). Market makers trading to accommodate the order imbalance must sell (buy). Thus, market maker order flow will be negative (positive) when stock returns are positive (negative), implying the negative relation.

However, it is questionable whether dealers actually supply liquidity as described in either model. While dealers may be meant to perform the socially beneficial function of liquidity provision, the institutional advantages granted to them also give the ability to act as super-efficient proprietary traders if they choose to. Dealer activities such as focusing on order flow information may enable them to deduce pricing information and trade accordingly.[1] Low transaction costs and

[1] Chae (2003) finds that dealers increase their price-sensitivity prior to information-revealing events, implying that they can deduce information about the events.

high transaction speeds may allow them to take advantage of opportunities that are not worthwhile to other market participants. Assuming that dealers want to maximize profits, their privileges may very well induce information as the primary motive for trade, rather than liquidity provision.

In practice, dealer trading is based on a complex set of interactions with other market participants in a variety of advantageous institutional setups. For example, New York Stock Exchange (NYSE) specialists are dealers that trade exclusively in a single stock. They are mandated to promote "stable and orderly" markets within an open-outcry system. In return, each is the central access point for almost all market participants who trade in their stock. Like dealers in other markets, NYSE specialists have much discretion over which trades to participate in (i.e. they do not blindly fill every single order immediately) and are granted special privileges, particularly in their access to order flow. Due to a lack of detailed specialist trade data, we have little idea whether they increase liquidity provision, and we know few details about the empirical relations between their order flow and stock prices.

Contrary to theory and intuition, our main finding is that the contemporaneous correlation between weekly dealer order flow and stock returns is strongly positive. This implies that dealers do not provide liquidity on a weekly frequency. Furthermore, using detailed intraweek transaction price and quantity data, we find that dealers earn significant excess returns. These excess returns are driven by information profits, rather than by market-making profits.[2] This information-driven profitability reinforces the main result by showing that dealers do not provide liquidity within the week. It also highlights the magnitude of the costs of allowing dealers institutional trading advantages. All the results strongly suggest that dealers are informed traders, since only informed traders should have positive price effects and such high excess returns driven by information.

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[2] Definitions of information profits and market-making profits are detailed in Section II.

These results have a few major policy and research implications. First, the common perception that dealers trade primarily to provide liquidity should be closely re-examined. Second, the mandate to provide liquidity (as NYSE, NASDAQ, and other dealers have) has a large shadow cost. For example, the NASDAQ requirement that dealers must always maintain two-sided quotes at reasonable depths is a costly restriction. Dealers with such constraints to provide liquidity may try to strategically minimize this cost; in other words, dealers may provide liquidity only to the extent that regulatory agencies require. Accordingly, future research and institutional policy about dealers should consider whether the advantages given impart the incentive to provide liquidity, and whether the cost of inducing this social function is worthwhile.

In most theory models of dealer trades, dealer roles and profits are analyzed assuming that they trade primarily as market makers. Given this basic premise, these models show that dealers take into account asymmetric information and hold order imbalances as their own inventory for potentially extended periods. In return, they are compensated with an amount related to half of the bid-ask spread[3] for each trade. The short list of empirical research about dealer trades also takes as given that dealers are market makers and analyze the data as such. These studies, including Ho and Macris (1984), Madhavan and Smidt (1993), and a few others, typically focus on high-frequency datasets and phenomena. They often have data for very few dealers (sometimes one) and very short time periods (sometimes a few weeks). Accordingly, these studies focus on short-horizon issues, such as determining components of the bid-ask spread, analyzing price-discreteness effects, and disentangling high-frequency information and inventory effects. However, there are potential problems arising from the use of such specific data. Idiosyncrasies in inventory management

[3] Glosten and Milgrom (1985) shows that bid-ask spreads may be caused by the information disadvantage of dealers.

strategies and information processing may dominate results when studying individual dealers, and trading patterns during very short time periods may not accurately reflect typical patterns.

To the best of our knowledge, ours is the first study to address the question of whether institutional advantages granted to dealers give them the incentive to provide or take liquidity. We use a unique and comprehensive dataset of weekly dealer trades, transaction prices, and inventory, over a five-year horizon. We aggregate trades across all dealers in the market to lessen effects of individual dealer idiosyncrasies, and we use over 5 years of data to mitigate period-specific relations. In addition, our use of weekly data rather than higher-frequency data helps to mitigate high-frequency microstructure effects in prices, such as bid-ask bounce.

Section 2 describes the dataset and market in detail. Section 3 defines the hypotheses and corresponding empirical tests. Section 4 documents the test results. Section 5 concludes with a brief summary, institutional implications, and directions for future research.

2. Data and Markets

2.1. Database

We use the Taiwan Economic Journal (TEJ) database of equities traded on the Taiwan Stock Exchange (TSE) from January 1997 to January 2002. In particular, we use weekly price and dealer trade data. This is a comprehensive dataset of all individual dealer trades, including inventory levels, gross buys (and sells), and average gross buy (and sell) prices. This unique data allow us to explore dealer trading and profits in great detail. To better understand this data, we first list some TSE summary statistics in Table 1 and then describe the institutional setup of the TSE.[4]

[4] All information regarding the TSE, SFC, and financial system in Taiwan is sourced directly from the TSEC website at http://www.tse.com.tw/docs/eng_home.htm, the TSEC Fact Book (2002), and the TSEC Annual Report (2002).

INSERT TABLE 1

Table 1 illustrates the clear pattern that large-cap stock returns were higher. The average market cap of the largest quartile is roughly (in New Taiwan Dollars) NT$70 billion, or roughly US$2.1 billion. The average market cap of the smallest quartile is about 33 times smaller. This illustrates the magnitude and variation across equity capitalizations in this market. We also see the pattern that smaller stocks had larger autocorrelations at almost all lags. Given the time period of 261 weeks (implying a standard error of autocorrelation estimates of roughly 0.062), there are several statistically significant values for lag 1 through lag 3 autocorrelations.

Total Market Capitalization of stocks listed on the TSE in 2001 was NT$10.25 trillion (roughly US$316 billion) in 2001 for 614 listed stocks. Annual market volume was NT$18.35 trillion, so dollar turnover in 2001 was 179% (compared to roughly 100% dollar turnover on the NYSE in 2001). While market capitalization and dollar volume obviously track market prices, share volume has remained relatively stable around 600 billion shares per year since 1996. Taiwan's equity market includes a wide range of participants, including local and international investment companies, banks, and individuals. The TSE is a large, well-regulated, highly liquid market in which many traders participate. Therefore, it is not as susceptible to price manipulation or dominant informed trader effects as other emerging markets are.

2.2. TSE Background and Institutional Setup

The Taiwan Stock Exchange Corporation (TSEC) was established in 1961 as a private institution overseen by the government. The TSEC has operated the TSE, the sole centralized stock exchange for listed securities in Taiwan, since its founding. In 1985, the original open outcry trading system was replaced by a computer-assisted limit order system; and finally the Fully

Automated Securities Trading (FAST) system was implemented in 1993. FAST is a pure limit order system with similar price/time priorities and trading rules as other limit order markets, such as the Paris Bourse and Toronto Stock Exchange. Trades are processed through a series of call auctions executed every 30 seconds. The opening call auction is similar to that on the NYSE, with the opening price determined chosen to maximize trading volume on the opening trade. There is no price limit for the opening call auction, but over our data sample there was a 2-tick price change limit on subsequent call auctions[5] and a 7% limit on daily price fluctuations. It is worth noting again that using weekly data mitigates many of the high-frequency microstructure issues associated with particular institutional setups (bid-ask bounce, discrete prices, etc.). Therefore, we do not explicitly consider these issues in our analysis.

Both listed (TSE stocks) and over-the-counter (OTC stocks) stocks are traded on the TSEC platform under the same trading rules. TSE stocks meet more stringent stability and size requirements, and the value-weighted performance of TSE stocks determines the TAIEX index. TSE stock trading is restricted to occur only on the TSEC platform, while OTC stocks may be traded off the system at prices negotiated between parties (the 7% daily price change limit still holds, but 2-tick rule does not). However, in practice, most OTC stock trades take place on the TSEC platform. Our data do include all trades executed on the TSEC system (all TSE stock trades and most OTC stock trades). Trade data are collected and recorded by the Securities and Futures Commission (SFC) and reported to the TEJ, insuring completeness and reliability.

2.3. TSEC Dealers

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[5] Tick sizes and stock prices are in NT$, in format: Tick(stock price bounds) = tick_value. Tick($S<5$) = .01; Tick($5\leq S<15$) = .05; Tick($15\leq S<50$) = .1; Tick($50\leq S<150$) = .5; Tick($150\leq S<1000$) = 1; Tick($S\geq 1000$) = 5.

Only two types of institutions may submit trades directly to the TSEC trade execution system: TSEC Brokers and TSEC Dealers. All other individual and institutional trades must be submitted through TSEC Brokers. Brokers have access to the TSEC system purely to facilitate customer trades in exchange for commissions. They are not allowed to trade on their own accounts, and their trade data is not publicly available.

TSEC Dealers are institutions that trade exclusively on their own accounts. The minimum capital required to be a Dealer is NT$400 million (approximately US$12 million), and NT$10 million (approximately US$350 thousand) must be left in an interest-bearing account as a security deposit. Dealer access to the TSEC is for proprietary trading purposes only, and their namesake portrays the SFC's desired role for them as liquidity-providing market makers. However, they have no explicit mandate to provide liquidity or price stability, (as NYSE Specialists and NASDAQ Dealers have) so they are almost unrestricted in their trades. Their only trade restriction is that they cannot short sell securities. Since they are afforded access to the TSEC system and are explicitly forbidden to trade on insider information, their trade data are readily available. See Table 2 for summary statistics about TSEC Dealer trades and Figure 1 for Dealer trading dollar volume percentiles.

INSERT TABLE 2 and FIGURE 1

As shown in Table 2, the number of dealers during our sample period ranged from 49 to 72. There is a noticeable 1-week autocorrelation in aggregate dealer net turnover[6], which decays rapidly. Average weekly net turnover was -0.009%, implying that dealers generally sold a little

[6] Turnover carries the implication of a standardized measure of unsigned trading volume. However, we use "net turnover" to indicate standardized dealer order flow, defined as [shares bought – shares sold] / [shares outstanding]. Similarly, "gross turnover" is defined as [shares bought + shares sold] / [shares outstanding].

over the sample period, while average weekly gross turnover was 0.226%. Average weekly net dollar volume was –NT$440 thousand, and average weekly gross dollar volume was NT$41.6 million. TSEC Dealers accounted for roughly 2% of total share trading volume[7]. Figure 1 illustrates the cross-sectional difference in dealer trading activity, plotting dollar volume at the 10%, 50%, and 90% levels.

TSEC Brokers and Dealers had strictly separated roles during our sample period, meaning an institution could only perform one of these functions.[8] Therefore, we do not consider moral hazard or other effects of potential front-running by brokers.

2.4. Dealer Transaction Speed and Cost Advantages

Only TSEC Brokers and Dealers have direct connections to the TSEC computer trade execution system, and they can enter trades as fast as they can key them in. They also receive detailed transaction reports instantly upon trade execution. All other traders have to trade through Brokers as an intermediary, and for most of the sample period internet trading was not widely available. Hence, the actions required for a typical investor's trade consisted of making a phone call and describing the trade to a broking agent, the broking agent transmitting the trade to the Broker's order-entry person, and the order entry person keying in the order. Confirmation of the trade occurred after the TSEC trade sheet was sent from the trading room to the broking agent and the broking agent had time to call back the customer. For many customers, trade confirmation did not occur until the customer received the trade sheet in the mail. Clearly, TSEC Dealers had a large advantage in trade execution and confirmation speed before internet transactions, and even now they still enjoy a significant advantage over internet traders who must interact with brokers.

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[7] From 1997 to 2001, TSEC dealer trades accounted for only 1.37% to 1.94% of total dollar trading volume.
[8] Since 2002, there have been regulatory moves to relax this separation rule. However, searching by name, we did not find any broker-dealers at the end of 2002.

Capital gains taxes have been exempted in Taiwan since 1990. Instead, stock sellers are levied a tax of 0.3% by the TSEC. Brokers can set their own commission rates up to a ceiling of 0.1425% of the value traded, and most set commissions very close to this rate. Since Dealers do not have to trade through brokers, they avoid this brokerage cost. Therefore, TSEC Dealers had not only an advantage in trade execution speed, but they also had a discount of about 28.5 basis points on round-trip trading costs relative to other market participants.

2.5. Order Flow Information

Quote from TSEC website in October 2002, "…the current order book is a black box where no unexecuted volume is disclosed (to the public). Starting July 1st of this year, the volume of unexecuted orders at best bid and ask prices will be disclosed so that market participants can make an informed judgment when placing orders. Beginning 2003, the volume of unexecuted orders of the 5 best bid and ask prices will be disclosed as well." Therefore, only very recently has any order book information been available to the public. The only order flow information available over our sample period was quotes of execution prices and aggregate daily volume. Other "ticker-style" order flow information was also available through fee-based terminals. It may be an interesting event study to explore the structural changes in the market caused by the recent changes in market transparency, but that is not within the scope of this paper.

2.6. Similarities to Other Markets

Taiwan is just one of many countries whose major stock exchanges are pure limit order markets. Other examples include Canada, France, Germany, Korea, and others. Even the NYSE and NASDAQ have significant portions of their market that work as limit order aggregation mechanisms via ECNs. Though there may not always be explicitly called "dealers" in other markets, it is a common assumption that there are agents in every market looking to profit by accommodating order imbalances. These agents typically have no inside information and no exogenous need for immediate trade, regardless of the particular institutional setup or location. We conjecture that the basic results of this paper should extend to such agents in other pure limit order markets and “limit order market segments” (such as ECNs in US markets) of dealer/specialist markets.

The basic results are also likely to extend to specialists and dealers in non-limit order markets, as long as the specialists or dealers have discretion over which trades to participate in and are granted institutional trading advantages. The basic premise is that if specialists and dealers have discretion over which trades to participate in, then they implicitly also have discretion whether to make markets or to trade on information. We hope to confirm our results in other markets given the eventual availability of reliable data in other markets.

3. Hypotheses

3.1. Hypothesis 1: Dealers Trade as Liquidity-Providing Market Makers

Most models of dealer trades imply that when dealers act as market makers to provide liquidity, there will be a negative relation between stock returns and aggregate dealer trades. Our primary hypothesis is based on this implied relation. The intuition is the following: as overall demand from all informed and uninformed traders increases (decreases), dealers providing liquidity is tantamount to dealers selling to (buying from) the rest of the market. Insofar as other traders have informational or mechanical price impact, the stock price will increase (decrease) while dealers are selling (buying), creating a negative contemporaneous relation between the returns and dealer order flow.

Consider two of the seminal models of dealer trading, Kyle (1985) and Grossman and Miller (1988). Kyle explores the inference problem and trading demands of uninformed market makers and informed traders, with noise traders essentially adding uncertainty. In his model, informed traders submit trades x in the direction of their information based on their trading aggressiveness, uninformed submit trades u for exogenous reasons, and market makers trade against the net demand (if net demand is $x + u$ then market makers trade $-x - u$) with a price impact determined by informed plus uninformed trader demand. This price impact will be in the direction of the net demand $x + u$, defined by the optimal (positive) market depth λ provided by the market maker. This price impact exists regardless whether the net demand in a given period is driven by informed or uninformed traders. As long as the ex-ante price is fair, the contemporaneous return is negative (positive) when a Kyle market maker buys (sells) shares; i.e. market maker order flow and security returns are negatively correlated.

Grossman and Miller (1988) consider dealer trading from an inventory risk perspective. Market makers are willing to provide liquidity when there is a net trade imbalance because they can transact at a superior price. The greater the imbalance, the better the price they can transact at. In return for holding a suboptimal inventory for a potentially extended period of time, they are rewarded with a premium that will be realized whenever the net trade imbalance returns to zero. Essentially, the model predicts that liquidity-providing market makers buy at lower than fair prices and sell at higher than fair prices. For example, assume the ex-ante price is fair and no information is revealed. Grossman and Miller market makers will only buy (sell) at a price below (above) fair value, so the price decreases (increases) when they buy (sell). Eventually, when the order imbalance disappears and they sell (buy), they do so at the higher (lower), fair price. Thus, Kyle (1985) and Grossman and Miller (1988) show that both asymmetric information and inventory models of dealer trades imply the same negative contemporaneous relation between dealer trades and security returns.

Our primary test uses a slightly modified vector auto-regression (VAR) of dealer order flow and stock returns to isolate this contemporaneous relation and to give insights about other predictive relations. In a typical VAR, only lagged variables are included as independent variables, but we include the contemporaneous dealer order flow in the return regression (and vice versa) since this is precisely the relation we are interested in. By using the VAR, we can measure the contemporaneous correlation while controlling for momentum or contrarian effects and potential price impact of dealer trades.[9] Our basic VAR specification is shown in Equations (1) and (2), where r is stock return and x is dealer order flow.

$$r_t = \alpha + \sum_{i=1}^{\infty} A_i r_{t-i} + \sum_{j=0}^{\infty} B_j x_{t-j} + \varepsilon_t \tag{1}$$

$$x_t = \alpha + \sum_{k=0}^{\infty} C_k r_{t-k} + \sum_{l=1}^{\infty} D_l x_{t-l} + \varepsilon_t \tag{2}$$

We estimate this VAR with both raw returns and index-adjusted returns for robustness. Dealer order flow is defined as aggregate dealer net turnover, or [net shares bought by dealers] / [shares outstanding]. Lo and Wang (2000) describe how this standardized measure of dealer order flow controls for shares outstanding and provides for cleaner interpretation of empirical results relative to share or dollar order flow. Since individual dealers have unique considerations such as inventory management and investment strategies, we aggregate order flow across dealers in each period to reduce the effects of dealer idiosyncrasies.

As a practical matter for empirical applications of VARs, i, j, k, and l, are chosen as finite lags. There is no standard method to determine the “correct” number of lags to include in such a regression. We include six lags, which is enough to study and correct for predictive relations of up to six weeks. As previously mentioned, our modification is to include contemporaneous order flow and return (j=0 and k=0) because these are the primary coefficients we are interested in.

[9] Hasbrouck (1991) offers a clear discussion of the general advantages and disadvantages of the VAR. Though there are significant differences in the tests between this paper and his, many of Hasbrouck’s general arguments help justify our own implementation of the VAR. For robustness, we also run simple correlations and univariate regressions of the contemporaneous relation between stock returns and dealer turnover.

In the context of the regression specification, *Hypothesis 1* can be restated as follows: B_0 and D_0 have negative sign. This would be consistent with dealers that provide liquidity.

3.2. *Hypothesis 2: Dealers Earn Excess Returns*

After establishing whether dealers provide liquidity, we test the profitability of dealers in aggregate to determine whether they earn excess returns. Any outcome from testing *Hypotheses 1* would be relatively benign if dealers are not any more profitable than the average market participant. However, if dealers are making excess returns using their institutional advantages, then this is a direct social cost of providing them these advantages. Since we have detailed intraweek transaction price and quantity data, we are able to test exact dealer profits much more accurately than most previous studies. In particular, we can disentangle returns attributable to information and to market-making.

In each period, we split dollar profits and returns into three components: information, market-making, and mixed. The dollar profits from each of these sources is calculated as described below and then converted to returns. The base value for the return is defined in each period by the value of the inventory held at the beginning of the current period (or equivalently, at the end of the previous period). The total dollar profit is the sum of the three dollar profit components, and the total return is the sum of the three return components.

To calculate the dollar profit of each component in a particular time period, we first split the stocks into those in which aggregate dealer net trading was positive and negative. The formulas for profit breakdown of a single stock in week t are shown below.

$$\prod = [InformationComponent] + [MarketMakingComponent] + [MixedComponent] \quad (3)$$

$$\prod(NetTrade+) = [INV_{t-1} * r_t] + [GrossSell * (P_{sell} - P_{buy})] + [NetBuy * (P_t - P_{buy})] \quad (4)$$

$$\prod(NetTrade-) = [INV_t * r_t] + [GrossBuy * (P_{sell} - P_{buy})] + [NetBuy * (P_{t-1} - P_{sell})] \tag{5}$$

Equations (4) and (5) denote profits from the cases where dealer net trading is positive and negative, respectively. INV_{t-1} (INV_t) is the share inventory level at the beginning (end) of the period t; r is the return on the stock; *GrossSell* (*GrossBuy*) is the gross shares sold (bought); P_{sell} (P_{buy}) is the average sell (buy) price for the shares sold (bought); *NetBuy* is the net shares bought; and P_t (P_{t-1}) is the price at the end (beginning) of the period. The terms in brackets represent profits from information, market-making, and mixed, respectively.

Information dollar profits are defined as the increase in value of the inventory held for the entire period. These profits can be attributed to information because dealers were committed to hold the inventory for an extended period (at least the entire week), indicating they believed that such positions in the stocks might be profitable. If dealer order flow in a given stock is positive (negative), then the amount held for the entire period is the inventory from the beginning (end) of the period.[10] The dollar profits on the inventory are calculated based on the return of the stock and this definition of shares held for the entire week.

Market-making profits are dollars earned from shares bought and sold in the same period. These profits are attributed to market-making because of the nature of providing short term liquidity. Providing short-term liquidity is tantamount to buying when there are too many sellers in the market and selling when there are too many buyers. In each case, the goal is to trade at an advantageous price due to the order imbalance and to undo the position when the imbalance disappears. This is equivalent to the famous quote, "Buy low, sell high!" To the extent that dealers are able to first buy and then sell (or vice versa) shares of a security within the same week, they are trying to do just that. If dealer net trading is positive (negative), then the relevant number of shares

[10] Recall the short sale constraint prohibits negative positions.

is the dealer gross sell (buy) amount. Since we have actual transaction prices for the gross buys and sells, we can calculate a very exact estimate of the dollar profit from these market-making trades.

Mixed dollar profits exhibit inseparable features of both inventory and market-making profits, and they are attributable to the net dealer trade in a stock. If net dealer trading is positive, then dealers bought the stock during the week and held it as inventory until the end of the week. If net dealer trading is negative, then they held inventory from the beginning of the period and sold sometime during the week. Mixed profits are attributable to information to the extent that these shares are held for part of the week, but they are attributable to market-making to the extent that dealers traded at advantageous prices caused by order imbalances.

Once we calculate the dollar profits from each stock in a single period, we sum the profits across stocks. The relevant base for conversion to return is the inventory value of all dealer holdings at the beginning of the period. We report the time-series average weekly returns, both raw and adjusted for the value-weighted index return. We also report subgroup analysis by stock capitalization.

3.3. Hypothesis 3: Dealers Infer Relevant Pricing Information

Because dealers focus attention on order flow information, it is possible that they can infer material pricing information. Though we cannot directly test this hypothesis, two manifestations of this would be significant return predictability of dealer trades and significant profitability of dealers. No further tests are required to draw these conclusions; we simply reinterpret the results of testing *Hypotheses 1* and 2.

First, if aggregate dealer order flow has significant predictive price effects, then this would indicate that dealer trades contain information. By observing the lagged order flow coefficients in the return regressions from *Hypothesis 1*, we can determine whether such price effects exist. Furthermore, we can even conjecture likely trading strategies. For example, if prices continually drift in the direction of dealer trades, this would indicate that dealers "under-trade" on the information they infer and they do not reveal the full information set they have with their trades. On the other hand, if prices tend to drift in the opposite direction of dealer trades, this indicates that they "over-trade" on their information and possibly employ positive-feedback strategies[11].

Second, if dealers are profitable relative to appropriate benchmarks, then it is likely that their advantages in execution efficiency or access to information are driving the profits. Tests for *Hypothesis 2* will indicate whether dealers are earning excess returns. By splitting profits into components derived from information and market-making, we can infer whether it is dealer information that drives profits.

The interpretations in this hypothesis will only be suggestive of whether dealers can truly infer material pricing information. However, we feel it is an important question, and we attempt to address it in such a suggestive way until better tests are devised.

3.4. Hypothesis 4: Dealers Trade More During Periods of Severe Order Imbalances

If dealers are performing the function of providing liquidity, then they should trade more when order imbalances are severe. Anecdotally, the correlation between order imbalance severity and periods of high volatility or kurtosis is high. Numerous media articles and academic papers point out that there are very few buyers during market crashes, even after prices drop below "fundamental" prices. Literature about market crashes and the role of institutions, such as Gennotte and Leland (1990), offer explanations for the lack of liquidity during periods of extreme volatility. Not only is the social function liquidity provision most important to other market participants during these periods, it is also these periods (when prices have likely diverged from

[11] Delong, Shleifer, Summers, and Waldmann (1990a) show that informed traders may "overtrade" relative to their information, while typical models show that informed traders "undertrade" to strategically minimize information release.

fundamentals) during which expected profits from providing liquidity should theoretically be the highest. Therefore, if market makers are providing liquidity by accommodating order imbalances, we should observe greater dealer trade activity during periods of higher volatility and kurtosis.

For each month, indexed by *t*, we calculate volatility and kurtosis of daily returns as well as average daily gross dealer trading volume (both turnover and dollar volume) for each stock. The following is the simple regression specification:

$$volatility_t = \alpha + \beta volume_t + \varepsilon_t \tag{6}$$

$$kurtosis_t = \alpha + \beta volume_t + \varepsilon_t \tag{7}$$

We implement the regressions as in Fama and MacBeth (1973). First we run cross-sectional regressions for each time period. Since each cross-sectional regression has a different number of observations depending on the number of stocks that dealers traded in the period, we calculate weighted (by degrees of freedom) time-series parameter estimates and t-statistics. Our null hypothesis that dealers trade more when volatility and kurtosis are higher would imply positive values of β for both the volatility and kurtosis regressions.

3.5. Hypothesis 5: Dealer Trades Are Contemporaneously Correlated

To justify our cross-sectional aggregation of dealer trades in the previous tests, we now test whether dealer trades are contemporaneously correlated. If so, then aggregation helps to isolate general relations and mitigate the effects of trades made for idiosyncratic reasons. If not, then dealers are simply a random set of market participants trading for wholly idiosyncratic reasons. In this case, aggregating dealer trades would simply pick up the trading patterns of the largest dealers. Contemporaneous correlation between traders' order flow has been tested in several papers exploring the concept of herding[12], such as Wermers (1999). The consensus benchmark used in these papers is the Lakonishok, Shleifer, and Vishny (1992) (henceforth LSV) measure. Essentially, their measure captures the contemporaneous correlation between dealer trades while correcting for the probability to find such correlation in random data. The original LSV herding formula for a single security *i* in a single time period *t* is shown in Equation (8).

$$H(i,t) = \left| \frac{B(i,t)}{B(i,t)+S(i,t)} - p(t) \right| - AF(i,t) \tag{8}$$

$B(i, t)$ and $S(i, t)$ are the numbers of buyers and sellers, $p(t)$ is the expected proportion of buyers in the current time period (calculated as the proportion of buyers across all stocks in the period), and $AF(i, t)$ is an adjustment factor equal to the expected value of the first term (inside absolute value bars) given the null of no herding and a binomial distribution of $B(i, t)$ vs. $S(i, t)$, with probability of $B(i, t)$ equal to $p(t)$. The typically reported measure is $\overline{H}$, or the average of $H(i, t)$ across all stocks and time periods. This measure should only be applied to specific group of traders, since, by definition, herding does not exist when aggregating all traders.

We calculate $\overline{H}$ once with $p(t)$ as originally conceived by LSV, as the proportion of buyers across all stocks and all dealers in time period t. This indicates a null that the probability a dealer will buy is the average probability that any dealer bought in a time period. This measurement of $p(t)$ corrects for market-level herding, whether caused by systematic fund inflows to the company or macroeconomic market-level news. This implies that if every single dealer buys (or sells) the same *n* securities and does not sell (buy) any, then the herding measure for every stock in the period will

[12] Though the word "herding" may have several interpretations and implications, we are interested only in herding as defined by the contemporaneous correlation between dealer trades.

be zero, even though this might instead reflect extreme herding.[13] For our modified herding measure, we recalculate the $\overline{H}$ with $p(t)$ equal to 0.5, reflecting a null that half of dealers would buy and half would sell in every period given no herding. This measurement of $p(t)$ is relevant if any market-level herding is driven by idiosyncratic, stock-specific reasons. This alternative null reflects herding caused by both individual stock herding and market-level herding, regardless whether market herding is driven by market-level news or stock-level news.

4. Empirical Results

We briefly summarize the primary empirical results, followed by a more detailed description of the tests and results. Our main finding is that aggregate dealer order flow exhibits a strong positive contemporaneous correlation with returns, inconsistent with both the theoretical models discussed earlier and the liquidity-providing role that dealers are supposed to play. Additionally, dealers earn consistently higher returns than the value-weighted stock index. This suggests that the advantages dealers are afforded in transaction speed and information access are advantageous in an economically significant way. These excess returns are driven by information, supporting the initial finding.

4.1. Test 1: Dealers Trade as Liquidity-Providing Market Makers

[13] Since LSV studied pension fund herding, there were specific reasons why their measure of $p(t)$ was appropriate for their study. In particular, correlated fund inflows and outflows to pension funds might cause macro-level herding even without any information. Since dealers do not have such correlated fund flows, we consider an alternate specification of $p(t)$ that does not correct for macro-level effects.

The primary result of this paper is the rejection of *Hypothesis 1*. Dealers do not act as liquidity-providing market makers. As discussed earlier, this is equivalent to finding a positive contemporaneous correlation between aggregate dealer net turnover and stock returns.

We use several methods to calculate the contemporaneous correlation, but the primary reported results are from the VAR.[14] To estimate the coefficients, *A*, *B*, *C*, and *D*, we implement a pooled regression and bootstrap to estimate standard errors[15]. We test several variations of the basic VAR, using raw vs. excess returns, TSE only vs. TSE + OTC stocks, and controlling vs. not controlling for overall market turnover. As a robustness check, we also run Fama and MacBeth (1973) style cross-sectional regressions with time-series significance tests for each variation of the VAR. These results are very similar in coefficients and t-statistics and are available on request. The main results of the pooled VAR estimations are shown below in Table 3.

INSERT TABLE 3

The t-statistics for the contemporaneous relation between return and dealer net turnover range from 5.800 to 9.285 in the return regressions and from 5.260 to 8.292 in the turnover regressions, indicating a strong significance regardless of the details of the specification. *Panel D* reports what we believe to be the "cleanest" results, in the following three ways. Excess (over TAIEX index) returns are used to eliminate systematic effects. OTC stocks are omitted to eliminate potential off-exchange price effects. Overall market turnover is included as a control variable, since it is

[14] In preliminary tests, we directly measured contemporaneous correlation between dealer net turnover and stock returns and ran univariate regressions between the two variables. The t-statistics from these tests range from 7.51 to 9.53.

[15] First, we randomly chose 261 time periods (our trade data includes 261 periods) with replacement. For each time period, we included all contemporaneous and lagged dealer turnover and stock return variables for all stocks. We ran the pooled regression with this dataset and recorded the coefficient estimates, and this comprised a single iteration. We ran 3,000 iterations of this procedure and calculated t-statistics with the standard deviations of the estimates.

shown in Wang (1994) that overall market turnover and stock returns have a strong relation. In the return regression of *Panel D*, the coefficient of contemporaneous Dealer net turnover is both economically and statistically significant, with a value of 1.539 and a t-statistic of 9.285. An interpretation is that for each 1% of shares outstanding purchased by Dealers in a given stock in a week, the return for that stock will increase by roughly 1.539%. The turnover regressions have a less intuitive interpretation, but also reflect the same strongly positive relation between returns and dealer order flow. The results and interpretations for other panels are similar, and each reconfirms the positive contemporaneous correlation.

One potential argument against the result is that perhaps Dealers simply have a mechanical price impact when they trade. Price impact typically refers to a mechanical change in price driven by a short-term supply or demand shock, such as a block trade might cause. For example, Holthausen, Leftwich, and Mayers (1987) find a tick-by-tick, contemporaneous price effect of 0.295% for downtick trades and 0.158% for uptick trades. However, they also find that by the end of the trading day, the permanent price effect has diminished to between 0.076% and 0.081% (for downtick and uptick trades, respectively).[16] Our results only include permanent weekly effects, which might reasonably be assumed even less than permanent daily effects. Mechanical price impact, while detectable on a tick-by-tick basis, is shown to be dramatically reduced by the end of the trading day, and so might be totally nonexistent over a week. However, the price effect 1.539% and t-statistic of 9.285 dwarf both the contemporaneous and permanent daily effect found by Holthausen, Leftwich, and Mayers. Since dealers trade less than 2% of dollar volume, it is unlikely that sheer trade size is driving this price effect. Results from *Test 2* will also suggest that information drives the positive relation.

[16] Holthausen et. al. (1987) study the total price effects as the sum of temporary and permanent price effects. Total price effects are the tick-by-tick price change from before a block trade, and permanent price effects are the price change from before a block trade to the same day closing price.

4.2. Test 1: Causality and Higher Frequency Implications

Since we have only weekly dealer trade data, the positive contemporaneous relation is conclusive evidence that dealers do not provide liquidity on a weekly basis. However, we also have a limited ability to draw the same conclusion at a higher frequency, given the lag 1 predictive relations in the VAR. If the lag 1 predictive relations are not strongly positive, this indicates that the positive weekly contemporaneous relation also holds for a higher frequency (perhaps up to daily). In *Panel D*, the coefficient of lag 1 order flow in the return regression is -0.113 with a t-statistic of -0.964. This indicates that order flow from the previous week (even from the last day of the previous week) does not at all cause an increase in current week return (even from the first day of the current week); if anything it reduces the current week return. The coefficient of lag 1 return on the order flow regression is 1.05×10^{-4} with a t-statistic of 0.585. This indicates that return from the previous week also has no statistically significant positive effect on order flow in the current week.

The conclusion most consistent with this evidence is that returns and dealer net turnover move together within the week. Results from *Test 2* using intraweek transaction prices and quantities will further strengthen our claim that dealers do not provide liquidity within the week, showing indirect evidence that the contemporaneous relation is positive at a higher frequency.

4.3. Test 1: Other Noteworthy Effects

Other interesting findings shown in the VAR are return autocorrelations, the predictive effect of dealer turnover on returns, and the overall market turnover control variable. First, almost all coefficients for 1 to 3 week autocorrelations in all panels of Table 3 are positive, and many are statistically significant. This confirms that the positive weekly autocorrelations shown in the summary statistics still hold after correcting for predictive effects. Taiwan is a market in which weekly momentum trading (transacted at closing prices) is profitable. We see that lag 1 dealer turnover autocorrelation is positive, meaning that dealers follow a 1-week momentum trading strategy, consistent with weekly momentum profitability.

Second, there seems to be strong predictive power of dealer turnover on stock returns. Although the contemporaneous relation is positive, the predictive relation is negative over the following 5-week period. Each coefficient only borders on statistical significance, but the consistently negative sign over 5 weeks indicates strong group-wise significance. The sum of these coefficients from *Panel A* through *Panel D* of Table 3 ranges from -37.2% to -97.8% of the original contemporaneous move, indicating strong economic significance. This indicates that after the initial price effect of dealer trades, there is a strong reversal over the next 5-week period.

INSERT TABLE 4

Table 4 shows the same VAR specification, this time in the more typical form without contemporaneous variables. In the return regression, the sum of the lagged dealer turnover coefficients is -0.50, and each individual coefficient is negative. This indicates that even in the traditional VAR framework, dealer trades have a negative predictive price effect. Chan and Lakonishok (1995) explicitly study the price impact of "package" trades[17] by investment management companies. Using a database of very large package trades, they find evidence of contemporaneous positive price impact but little evidence of the reversal we see.

Finally, the overall market turnover control variable has effects in both the return and turnover regressions. In the return regression from *Panel D* of Table 3, higher turnover is associated with

[17] A package is group of block trades in a single stock over possibly more than one day, all in the same direction.

higher excess return, consistent with predictions from Wang (1994). On the dealer net turnover regression, the t-statistic for overall market turnover is -2.953, indicating higher market turnover is associated with Dealers decreasing inventory. Given the short sale restriction, if market makers are truly providing liquidity, then true market makers should hold more inventory to provide liquidity during periods of high market turnover. Instead, this is additional evidence that dealers do not provide liquidity.

4.4. Test 1: Subgroup Analysis and Patterns

We estimate three subgroup variations of the basic VAR to further explore the main result. First, we sort stocks by size quartiles at the beginning of the previous year and test each of these size quartiles. See *Panel A* of Table 5 below for results.

INSERT TABLE 5

For each of the size quartile VAR regressions, we see that each of the coefficients for contemporaneous turnover, *x0*, is positive and generally increasing in stock size. The t-statistics are all increasing in stock size. This increasing pattern across stock size quartiles indicates that dealers trade less to provide liquidity and more on information for large-cap stocks. One likely conclusion is that provision of liquidity is not as necessary for large, liquid stocks, as it is for small, illiquid stocks. Another potential conclusion is that dealers are better able to detect material pricing information for large-cap stocks, and they trade accordingly.

In the second subgroup, we examine dealer participation directly by sorting stocks by dealer gross turnover in the previous year,[18] reported in *Panel B*. This time, the pattern across the coefficients for *x0* does not show an obvious relation, though the t-statistics again suggest that higher dealer turnover in a given stock is associated with stronger contemporaneous relations between dealer turnover and stock returns. The interpretation from the pattern in t-statistics implies that the more active dealers are in a stock, the more likely it is they are trading on information in that stock.

In the third and final subgroup, we sort dealers by dollar volume in the previous year.[18] The pattern across the coefficient for *x0* shows that large, active dealers have a larger contemporaneous price effect than small, inactive dealers. The negative coefficients for quartiles 1 (smallest) and 2 show that small dealers might provide liquidity, though neither coefficient is statistically significant.

4.5. Test 2: Dealers Earn Excess Returns

We find that dealers are profitable, with profits driven by information trading rather than market-making. Thus, we confirm *Hypothesis 2*. Table 6 summarizes the results.

INSERT TABLE 6

Panel A shows that average unadjusted weekly returns for dealers is 30.7 basis points (implying an annual return of about 15.96%) with a t-statistic of 1.035. We can see that this return is largely driven by information (returns from inventory held) rather than market-making (returns

[18] In the first year of our sample period (1997), we used the same-year sorting. The results using same-year sorting for every year are similar and not reported.

from positions opened and closed in the same week). The TAIEX value-weighted index average return over the same period was -7.2 basis points weekly (about -3.74% annually). Though this result is already conspicuous, it does not tell the entire story. We observe the same pattern in the stock size quartile results as in the summary statistics; dealers are more profitable in large stocks than small stocks. Information profits are increasing in stock size, though there is no discernable pattern in market-making profits.

Panel B sheds more light on the results by adjusting for the appropriate index return each week. The aggregate results are adjusted by the TAIEX value-weighted index return, and each size quartile is adjusted by the appropriate value-weighted quartile return. Dealer excess returns are 37.8 basis points weekly, (about 19.66% annually), with a t-statistic of 4.828. This statistical significance implies that dealers consistently outperform the TAIEX benchmark on a weekly basis. Upon closer inspection, only the excess return from the information component is statistically significant. This confirms that profits from inventory held are driving the consistent outperformance. Furthermore, the size quartile results show that total index-adjusted returns are also increasing in stock size. However, we now observe that market-making profitability clearly decreases in stock size. Dealers seem to profit more from information trades in large stocks and more from market-making in small stocks. Finally, *Panel B* also shows that dealers outperform the appropriate index in each stock quartile and profit component, except for market-making profits of the largest stocks.

The results across stock size are consistent with the following theories. First, small firms have less analyst and media coverage and therefore exhibit higher information asymmetry via less publicly circulated information. Insiders have a great information advantage for these companies, but they are restricted from releasing the information by trading. Therefore, it is difficult for uninformed agents such as market makers to extract information from order flow and earn information profits in small firms. Second, large-cap stocks are more liquid than small-cap stocks, since almost all traders (mainstream retail investors, institutional investors, index funds, etc.) participate in trading them. When there are perceivable order imbalances in large-cap firms, there are more potential agents willing to absorb the imbalance. Given this higher competition to provide liquidity, the liquidity provision for large firms does not have the same profit potential as for small firms. The natural implication of both of these theories is that dealers may be necessary only for small or illiquid stocks.

4.6. Test 3: Dealers Infer Relevant Pricing Information

Tests 1 and *2* are both suggestive that dealers do infer material pricing information. Hence we cannot reject *Hypothesis 3*. Based on the VAR used to test *Hypothesis 1*, we can also infer that there is some strategic trading involved in dealer trades. Based on *Test 1*, dealers have a strong positive contemporaneous price effect followed by a strong reversal effect. The magnitude of the reversal ranges from about 35% to 100% of the initial price effect, depending on the regression specification. This indicates that dealers overtrade on what information they have, potentially taking advantage of positive-feedback strategies. Based on *Test 2*, dealers are indeed profitable, and their profits are driven by the information component rather than the transaction (market-making) component. Given that dealers do not have explicit contracts or relationships with firms or investment banks, both of these results are highly suggestive that dealers somehow infer material pricing information from their focus on order flow information.

4.7. Test 4: Dealers Trade More During Periods of Severe Order Imbalances

Given that *Tests 1* and *2* showed that dealers do not provide liquidity, the interpretation of this hypothesis has changed. In any case, we find inconclusive evidence and partially reject *Hypothesis 4*. Dealers trade more when volatility is higher, but less when kurtosis is higher, though they are not trading to provide liquidity.

INSERT TABLE 7

In *Panel A* of Table 7, we report the results of the volatility regressions. Using dealer turnover as the independent variable, we find a coefficient of 3.904. On average, additional dealer turnover of 1% of shares outstanding during a given month is associated with 3.904% higher standard deviation of daily returns during that month. The t-statistic of 12.620 indicates a strongly significant relation. In *Panel C*, we observe that kurtosis is negatively related to dealer turnover. The interpretation of the coefficient of -479.721 is similar, and the t-statistic of -11.954 again indicates extremely high statistical significance. One reason for the strong kurtosis result is the 7% daily price change limit, and another is that dealers simply refuse to trade during extreme price moves. *Panels B* and *D* show similar relations using dealer dollar trading amount as the independent variable, though the t-statistics are lower.

These results indicate that dealers trade more when volatility is higher, but less during extreme price changes. Taken together with *Tests 1* and *2*, these results imply that dealer informed trading activity is more profitable during periods of high volatility, but that dealers are unwilling to accept the risks of trading during crashes and large price increases.

4.8. Test 5: Dealer Trades Are Contemporaneously Correlated

Our tests indicate cross-sectional dealer trade correlation of very similar magnitude as that found in previous studies; hence we confirm *Hypothesis 5*. LSV studies herding among pension funds, a group that presumably shares common sources of information and common trading strategies. They find an average herding measure of 2.7%, as well as a pattern that herding is stronger in smaller stocks than in larger stocks. Other studies, such as Wermers (1999), find similar results for mutual funds and other trading groups. Our results, as shown in Table 8, confirm both the decreasing relation with stock size and absolute magnitude of the overall average measure (2.24% with our modified measure and 1.33% with the original LSV measure). All results with both measures are statistically significant, including each of the size quartile results.

INSERT TABLE 8

LSV interprets that a measure of 2.7% indicates that on average in a given quarter for a given stock, 52.7% of pension funds bought (or sold) and 47.3% traded in the opposite direction. However, this interpretation is not entirely clear. For example, given the adjustment factor *AF*, the maximum value of the measure in the special case of 2 dealers would be 25%. This maximum would imply that 75% of dealers bought (or sold) and 25% traded in the opposite direction; even if dealers always traded together in perfect unison. However, such perfect correlation between trades should imply a measure of 50% instead. Therefore, in some sense, the LSV measure underestimates actual herding.

The focus of this paper is not to discuss the merits of the LSV measure. Instead, we use it only as a benchmark for comparison to investment funds and other groups that are known to have correlated trades. With the LSV measure (and our modification), we conclude that dealers herd to a similar extent as pension funds and mutual funds. Insofar as pension funds and mutual funds have common information and trading strategies, so do dealers.

5. Conclusions

We have shown that dealers do not provide liquidity to the market; instead, they trade on information. First of all, the contemporaneous correlation between dealer order flow and stock returns is highly positive, inconsistent with models of market maker trades. Additional interesting features of dealer trades include a long-term return predictive price effect of dealer turnover. Second, dealers earn significant excess returns which are in aggregate driven by the information component of profits. Patterns across stock size indicate that information profits are increasing in stock size and market-making profits are decreasing in stock size. One implication of these two results is that dealers infer relevant pricing information from their activities. Next, we explored higher moments of stock returns to gain further insight into when dealers trade. Dealers trade more when volatility is higher but less during periods of extremely severe returns (high kurtosis). Given the primary results, this gives the insight that it may be most profitable for informed traders to trade during periods of high volatility but not during extreme price movements. Finally, we justified our aggregation of dealer trades by establishing a significant contemporaneous correlation across individual dealer order flow.

5.1. Institutional Implications

The institutional setup of providing dealers with low transaction costs, high transaction speed, and access to order flow information, is clearly valuable. As anecdotal evidence, one needs only to note the premiums paid for seats on the NYSE, the profitability of National Association of Securities Dealers Automatic Quotation (NASDAQ) Dealers, and the expanding role of ECNs. These advantages create an indirect, but real, transfer of wealth from other market participants. If dealers are to have such valuable advantages, then they should be held to the socially beneficial function of providing liquidity, perhaps via narrow bid-ask spreads at reasonable depths at all times. This is, in fact, very similar to the liquidity mandate of NYSE Specialists and NASDAQ Dealers.

On the other hand, one reason why some markets provide benefits to dealers is to compensate them for bearing the adverse selection risk involved in providing liquidity by posting limit orders. As markets move toward greater transparency of order flow information (public limit order books, etc.), dealers lose a large part of their advantage. As this advantage is reduced, so should the severity of the mandate to provide liquidity. One way to do this is to lessen the share depths or increase the bid-ask spreads required. Markets that are making moves toward more transparency and less dealer trade execution advantages should consider this. In particular, as US market transparency continues to increase via public ECN limit order books and regulatory requirements, US dealer liquidity mandates should be made less stringent.

Our findings from studying unconstrained dealers (with no liquidity mandate) indicate that there is a large shadow cost to the liquidity mandate. Thus, dealers with such mandates are likely to strategically minimize this cost, perhaps by choosing which trades to be counterparty to or by disallowing naturally crossing trades (that other market participants would theoretically be willing to trade themselves) to execute. Unfortunately, such strategic activities lessen the social benefits that dealers provide.

In the final analysis, the advantages afforded to dealers to provide this social benefit should be commensurate with the risks they take and services they provide, and if they cannot provide this service then they may be obsolete. In particular, our evidence that dealers profit most from information instead of market-making in large-cap stocks, indicates that dealers may not be necessary to ensure ample liquidity provision in these stocks. Accordingly, there may no longer be a need to provide institutional trading advantages for dealers in large, liquid stocks. However, since dealers do profit from making markets in smaller, less liquid stocks, they may still play a valuable role in these stocks. This intuition can also be applied on a larger scale: in large, liquid, and relatively stable markets, the designation of a special group of traders to provide liquidity is not as critical as in small, illiquid markets.

5.2. Future Research

The results from this paper show conclusive evidence that unconstrained dealers do not provide liquidity on a weekly basis, and they are suggestive that they do not on higher frequencies as well.

However, our findings of positive dealer profits from market-making trades indicate that dealers may provide liquidity at a very high frequency (perhaps hourly or tick-by-tick). We hope to test this upon availability of high frequency dealer trade data.

Several important institutional changes have been implemented on the TSE since January 2002 that will provide for interesting event studies. In particular, we will study the effects of regulatory moves allowing broker-dealers and of transitioning from a fully opaque order book system to a more transparent system (5 levels of the best bid and ask prices have been available since 2003). These institutional changes have unclear effects on market liquidity and transactional efficiency that warrant investigation.

Finally, this paper focuses on aggregate dealer trading and behavior to establish that dealers are information traders that do not provide liquidity. Wang (2004) further explores cross-sectional trading and information trading of dealers.

References

Chae, Joon, 2003, Trading volume, information asymmetry, and timing information, Unpublished Ph.D. thesis (MIT, Cambridge).

Chan, Louis K. C., and Josef Lakonishok, 1995, The behavior of stock prices around institutional trades, The Journal of Finance, 50, 1147-1174.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990a, Positive feedback investment strategies and destabilizing rational speculation, The Journal of Finance, 45, 379-395.

Fama, Eugene, and James MacBeth, 1973, Risk, return, and equilibrium: empirical tests, Journal of Political Economy, 71, 607-636.

Gennotte, Gerard, and Hayne Leland, 1990, Market liquidity, hedging, and crashes, The American Economic Review, 80, 999-1021.

Glosten, Lawrence R., and Paul Milgrom, 1985, Bid, ask, and transaction prices in a specialist market with heterogeneously informed agents, Journal of Financial Economics, 14, 71-100.

Grossman, Sanford J., and Merton H. Miller, 1988, Liquidity and market structure, The Journal of Finance, 17, 617-633.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, The American Economic Review, 70, 393-408.

Hasbrouck, Joel, 1991, Measuring the information content of stock trades, The Journal of Finance, 46, 179-207.

Ho, Thomas, and R. Macris, 1984, Dealer bid-ask quotes and transaction prices: an empirical study of some AMEX options, The Journal of Finance, 39, 23-45.

Holthausen, Robert W., Richard W. Leftwich, and David Mayers, 1990, Large-block transactions, the speed of response, and temporary and permanent stock-price effects, Journal of Financial Economics, 26, 71-95.

Kyle, Albert, 1985, Continuous auctions and insider trading, Econometrica, 53, 1315-1336.

Lakonishok, Joseph, Andrei Shleifer, and Robert W. Vishny, 1992, The effect of large block transactions on security prices: a cross-sectional analysis, Journal of Financial Economics, 19, 237-267.

Lo, Andrew, and Jiang Wang, 2000, Trading volume definitions, data analysis, and implications of portfolio theory, The Review of Financial Studies, 13, 257-300.

Madhavan, Ananth, and Seymour Smidt, 1993, An analysis of changes in specialist quotes and inventories, The Journal of Finance, 48, 1595-1628.

O'Hara, Maureen, 2002, Liquidity and price discovery, Working Paper.

Scharfstein, David S., and Jeremy C. Stein, 1990, Herd behavior and investment, The American Economic Review, 80, 465-479.

Seyhun, H. Nejat, 1988, The information content of aggregate insider trading, Journal of Business, 61, 1-24.

Wang, Albert, 2004, A cross-sectional analysis of dealer profits, Unpublished Ph.D. thesis (MIT, Cambridge).

Wang, Jiang, 1994, A model of competitive stock trading volume, Journal of Political Economy, 102, 127-168.

Wermers, Russ, 1999, Mutual fund herding and the impact on stock prices, The Journal of Finance, 54, 581-622.

Tables and Figures

Table 1
Taiwan Stock Exchange Summary Statistics, 1997-2002

The table reports weekly summary statistics for stocks listed on the Taiwan Stock Exchange from January 1997 to January 2002. *Panel A* reports the number of firms, average share turnover, average market capitalization, and return statistics for the Value-Weighted Index (VW), Equal-Weighted Index (EW), and size quartiles (4 = largest). Size quartile returns are value-weighted. The unit of market capitalization is million New Taiwan dollars (NT$1,000,000). *Panel B* reports return autocorrelations for the same portfolios in *Panel A*. The standard errors for the autocorrelation estimates are roughly 0.062. Returns and turnover are weekly and expressed in percent.

Panel A: TSE Weekly Summary Statistics

		Turnover	Market Cap	Return		
	# Firms	(%)	(NT$mm)	Average	StdDev	Skew
VW	--	--	--	0.004%	4.272%	0.128
EW	670	0.226%	17,438	-0.022%	4.182%	-0.057
Quartile 1	121	0.277%	2,152	-0.767%	4.215%	0.016
Quartile 2	121	0.251%	5,073	-0.369%	4.619%	-0.150
Quartile 3	122	0.225%	10,737	-0.217%	4.520%	-0.221
Quartile 4	121	0.148%	70,471	0.127%	4.366%	0.194

Panel B: TSE Weekly Return Autocorrelations

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
VW	-0.035	0.098	0.117	0.003	-0.014	-0.004
EW	0.106	0.164	0.181	0.069	0.028	0.048
Quartile 1	0.216	0.206	0.242	0.122	0.058	0.091
Quartile 2	0.091	0.163	0.175	0.083	-0.001	0.054
Quartile 3	0.030	0.149	0.153	0.062	0.000	0.044
Quartile 4	-0.047	0.096	0.107	-0.001	-0.014	-0.002

Table 2
TSEC Dealer Trading Summary Information

The table reports summary information about TSEC Dealers from January 1997 to January 2002. *Panel A* reports the number of dealers at the beginning of each year. *Panel B* reports autocorrelation in aggregated dealer net turnover, first pooled across all stocks followed by mean and standard deviation across stocks. *Panel C* reports Fama and MacBeth (1973) style aggregate dealer trading statistics. First we calculate cross-sectional trading measures (net turnover, standard deviation of net turnover, skew of net turnover, etc.) across stocks for each time period. We report the time series number of observations, mean, standard error, minimum, and maximum for each of these cross-sectional measures. Turnover (Shares Traded / Shares Outstanding) is in percent and dollar volume is in NT$1,000s.

Panel A: Number of Dealers by Year

	1/1997	1/1998	1/1999	1/2000	1/2001	1/2002
Number of Dealers	49	59	70	72	60	58

Panel B: Autocorrelation of Aggregate Dealer Net Turnover

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
Pooled Autocorrelation	0.09	0.01	0.01	0.00	0.00	-0.01
Mean Autocorrelation	0.11	0.03	0.01	0.00	0.00	-0.01
Standard Deviation	0.26	0.22	0.18	0.17	0.17	0.15
N (Stocks)	914	907	899	888	884	885

Panel C: Aggregate Dealer Trading Statistics

Trading Measure	Weeks	Mean	Std Err	Minimum	Maximum
Mean Net Turnover	261	-0.009%	0.001%	-0.076%	0.068%
StDev Net Turnover	261	0.237%	0.006%	0.039%	0.695%
Skew Net Turnover	261	-0.090%	0.026%	-1.728%	1.736%
Mean Gross Turnover	261	0.226%	0.007%	0.017%	0.697%
StDev Gross Turnover	261	0.453%	0.027%	0.027%	3.593%
Skew Gross Turnover	261	0.715%	0.031%	0.183%	2.698%
Mean Net Dollar Volume	261	$ (440.3)	$ 317.6	$ (18,255.0)	$ 19,791.4
StDev Net Dollar Volume	261	$ 47,957.0	$ 1,428.8	$ 5,243.5	$ 126,370.2
Skew Net Dollar Volume	261	$ 0.1	$ 0.3	$ (16.8)	$ 13.9
Mean Gross Dollar Volume	261	$ 41,644.6	$ 1,506.4	$ 2,168.2	$ 128,097.9
StDev Gross Dollar Volume	261	$ 124,191.0	$ 4,686.1	$ 7,402.5	$ 449,826.5
Skew Gross Dollar Volume	261	$ 6.1	$ 0.1	$ 2.2	$ 12.9

Figure 1
Taiwan Stock Exchange Dealer Cross-Sectional Trading Activity
This figure is a time series plot of the weekly dollar trading volume by dealers (in NT$1,000,000). "10%," "50%," and "90%" refer to the cross-sectional dealer dollar volume percentiles, and each line plots the corresponding percentile trading volume for each week from January 1997 to January 2002.

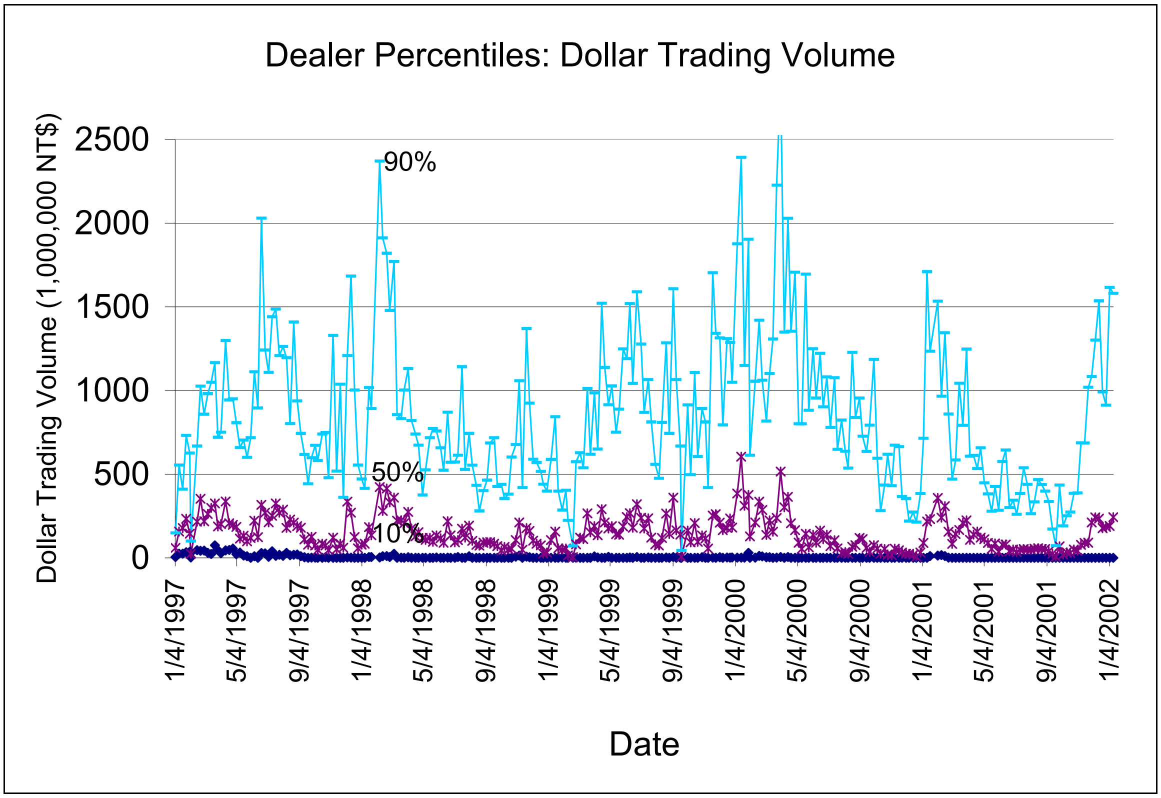

Table 3
Dealer Trade and Stock Return VAR

This table reports VAR regression coefficients for the following pooled regression specifications:

$$r_{n,t} = \alpha_r + \sum_{i=1}^{6} A_i r_{n,t-i} + \sum_{j=0}^{6} B_j x_{n,t-j} + \gamma TO_t + \varepsilon_{n,t} \qquad x_{n,t} = \alpha_x + \sum_{k=0}^{6} C_k r_{n,t-k} + \sum_{l=1}^{6} D_l x_{n,t-l} + \gamma TO_t + \varepsilon_{n,t}$$

r is weekly stock return (using raw return or excess over the value-weighted index), *x* is weekly aggregate dealer net turnover (net trade / shares outstanding), and *TO* is overall market turnover. *Panels C* and *D* control for overall market turnover. *Panel D* uses only listed TSE stocks. r0 – r6 refer to the regression coefficients on independent return variables (A_1-A_6 for the return regressions and C_0-C_6 for the dealer turnover regressions), and *x0 – x6* refer to the regression coefficients on independent dealer turnover variables (B_0-B_6 for the return regressions and D_1-$D_6$for the turnover regressions). **Bold** indicates statistical significance, i.e. |t-statistic| ≥ 2. Boxed indicates a group of lagged variable coefficients with consistent signs, which may indicate significant relations.

Panel A: TSE+OTC, Raw Returns

	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6
r	-0.002		0.034	**0.068**	**0.061**	0.011	-0.015	-0.001	**1.120**	-0.141	-0.214	-0.080	-0.260	0.020	-0.018
t-stat	-0.550		1.177	**2.459**	**2.272**	0.407	-0.558	-0.023	**5.808**	-1.003	-1.404	-0.602	-1.853	0.156	-0.157
x	**-0.099**	**9.55E-04**	-2.07E-04	-1.94E-04	-2.59E-04	-7.99E-06	9.62E-06	1.20E-05		**0.070**	0.002	0.004	-0.010	0.004	-0.011
t-stat	**-7.748**	**5.321**	-1.400	-1.241	-1.953	-0.066	0.069	0.094		**4.782**	0.179	0.469	-1.033	0.557	-1.284

Panel B: TSE+OTC, Excess Returns

	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6
r	-0.001		**0.035**	**0.043**	0.024	0.002	-0.004	-0.012	**0.946**	-0.203	-0.212	-0.165	**-0.296**	-0.049	0.038
t-stat	-0.404		**2.339**	**2.782**	1.850	0.130	-0.317	-1.002	**5.800**	-1.840	-1.959	-1.596	**-2.750**	-0.486	0.372
x	**-0.099**	**1.06E-03**	6.08E-05	-6.78E-05	-7.25E-05	1.75E-04	2.59E-05	6.64E-05		**0.070**	0.002	0.004	-0.010	0.004	-0.011
t-stat	**-7.965**	**5.260**	0.395	-0.460	-0.492	1.565	0.191	0.528		**4.817**	0.179	0.461	-1.048	0.575	-1.289

Panel C: TSE+OTC, Excess Returns, Control TO

	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6	TO
r	-0.002		**0.034**	**0.043**	0.025	0.003	-0.003	-0.011	**0.973**	-0.191	-0.203	-0.158	**-0.292**	-0.043	0.040	**0.495**
t-stat	-1.211		**2.266**	**2.798**	1.925	0.225	-0.225	-0.910	**6.084**	-1.744	-1.881	-1.524	**-2.724**	-0.432	0.385	**2.330**
x	**-0.083**	**1.10E-03**	7.81E-05	-7.03E-05	-8.63E-05	1.58E-04	7.49E-06	5.18E-05		**0.069**	0.002	0.004	-0.010	0.004	-0.011	**-0.007**
t-stat	**-6.796**	**5.488**	0.510	-0.477	-0.585	1.409	0.055	0.412		**4.806**	0.168	0.450	-1.052	0.564	-1.291	**-2.679**

Panel D: TSE, Excess Returns, Control TO

	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6	TO
r	**-0.004**		0.017	**0.037**	0.018	-0.006	0.001	-0.012	**1.539**	-0.113	-0.057	**-0.221**	-0.159	-0.024	0.011	**1.661**
t-stat	**-3.334**		1.060	**2.242**	1.369	-0.435	0.054	-0.958	**9.285**	-0.964	-0.502	**-2.108**	-1.399	-0.231	0.096	**4.879**
x	**-0.046**	**2.03E-03**	1.06E-04	3.12E-05	-6.35E-05	**2.90E-04**	-1.35E-05	1.31E-04		**0.053**	-0.010	-0.002	-0.016	0.001	-0.013	**-0.012**
t-stat	**-3.546**	**8.292**	0.585	0.174	-0.371	**2.173**	-0.083	0.881		**3.152**	-0.934	-0.184	-1.462	0.079	-1.372	**-2.953**

Table 4

Dealer Trade and Stock Return VAR, Lagged Independent Variables Only

This table reports VAR regression coefficients for the following pooled regression specifications:

$$r_{n,t} = \alpha_r + \sum_{i=1}^{6} A_i r_{n,t-i} + \sum_{j=1}^{6} B_j x_{n,t-j} + \gamma TO_t + \varepsilon_{n,t} \qquad x_{n,t} = \alpha_x + \sum_{k=1}^{6} C_k r_{n,t-k} + \sum_{l=1}^{6} D_l x_{n,t-l} + \gamma TO_t + \varepsilon_{n,t}$$

r is weekly stock excess return (over the value-weighted index), *x* is weekly aggregate dealer net turnover (net trade / shares outstanding), and *TO* is overall market turnover. Only listed TSE stocks are included, and TO is an overall market turnover control variable. r1 – r6 refer to the regression coefficients on independent return variables (A_1-A_6 for the return regressions and C_1-C_6 for the dealer turnover regressions), and *x1 – x6* refer to the regression coefficients on independent dealer turnover variables (B_1-B_6 for the return regressions and D_1-$D_6$for the turnover regressions). **Bold** indicates statistical significance, i.e. |t-statistic| ≥ 2. Boxed indicates a group of lagged variable coefficients with consistent signs, which may indicate significant relations.

TSE, Lags Only, Excess Returns, Control TO

	Intercept	r1	r2	r3	r4	r5	r6	x1	x2	x3	x4	x5	x6	TO
r	**-0.004**	0.018	**0.037**	0.019	-0.006	0.000	-0.012	-0.022	-0.064	**-0.214**	-0.192	-0.001	-0.001	**1.640**
t-stat	**-3.519**	1.109	**2.214**	1.372	-0.419	0.027	-0.972	-0.184	-0.554	**-1.979**	-1.636	-0.005	-0.008	**4.908**
x	**-0.054**	1.41E-04	1.06E-04	-2.60E-05	2.79E-04	-1.20E-05	1.07E-04	**0.053**	-0.011	-0.002	-0.016	0.001	-0.013	**-0.008**
t-stat	**-4.405**	0.799	0.613	-0.157	1.994	-0.074	0.724	**3.182**	-0.941	-0.229	-1.493	0.074	-1.354	**-2.221**

Table 5
Dealer Trade and Stock Return VAR, Subgroup Analysis

This table reports VAR regression coefficients for the following pooled regression specifications:

$$r_{n,t} = \alpha_r + \sum_{i=1}^{6} A_i r_{n,t-i} + \sum_{j=0}^{6} B_j x_{n,t-j} + \gamma TO_t + \varepsilon_{n,t} \qquad x_{n,t} = \alpha_x + \sum_{k=0}^{6} C_k r_{n,t-k} + \sum_{l=1}^{6} D_l x_{n,t-l} + \gamma TO_t + \varepsilon_{n,t}$$

r is weekly stock excess return (over the value-weighted index), *x* is weekly aggregate dealer net turnover (net trade / shares outstanding), and *TO* is overall market turnover. *Panel A* reports results for stock size quartiles (4=largest), sorting stocks by market capitalization at the beginning of each year. *Panel B* reports for stock quartiles (4=largest), sorting stocks by dealer gross turnover in the stock in the previous year (except in 1997, the 1997 sorting is applied). All specifications use only listed TSE stocks and include the overall market turnover control variable. r0 – r6 refer to the regression coefficients on independent return variables (A_1-A_6 for the return regressions and C_0-C_6 for the dealer turnover regressions), and *x0* – *x6* refer to the regression coefficients on independent dealer turnover variables (B_0-B_6 for the return regressions and D_1-$D_6$for the turnover regressions). **Bold** indicates statistical significance, i.e. |t-statistic| ≥ 2. Horizontal-$\boxed{\text{Boxed}}$ indicates a group of lagged variable coefficients with consistent signs, which may indicate significant relations. Vertical-$\boxed{\text{Boxed}}$ indicates a pattern across quartiles in the t-statistics that may indicate an economic relationship across quartiles.

Panel A: Stock Quartiles by Stock Size (4=largest)

	Quartile	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6	TO
r	1	**-0.007**		**0.061**	0.027	0.017	-0.005	0.011	-0.025	0.636	-0.036	**-1.207**	-0.036	-0.277	0.033	0.231	0.197
r	2	**-0.011**		0.020	0.015	0.014	-0.007	0.019	-0.013	0.599	-0.067	-0.005	**-0.472**	**-0.467**	**0.364**	0.185	**2.971**
r	3	**-0.009**		-0.004	0.035	0.002	-0.024	-0.015	-0.012	**1.656**	-0.025	0.049	-0.076	-0.084	-0.176	-0.106	**3.670**
r	4	**-0.005**		-0.021	0.026	0.017	-0.010	-0.015	-0.023	**2.681**	-0.036	0.169	-0.125	0.147	-0.239	-0.161	**4.642**
t-stat	1	**-2.983**		**2.466**	1.137	0.868	-0.251	0.583	-1.298	1.151	-0.090	**-3.342**	-0.118	-0.726	0.103	0.664	0.831
t-stat	2	**-6.427**		0.912	0.727	0.854	-0.370	1.105	-0.780	1.945	-0.349	-0.024	**-2.554**	**-2.184**	**2.104**	1.066	**7.032**
t-stat	3	**-6.706**		-0.193	1.919	0.104	-1.577	-0.885	-0.876	**8.416**	-0.137	0.285	-0.437	-0.487	-0.927	-0.591	**10.091**
t-stat	4	**-6.316**		-1.191	1.481	1.042	-0.616	-0.939	-1.519	**9.679**	-0.167	0.820	-0.599	0.689	-1.230	-0.719	**11.062**
x	1	**-0.109**	6.11E-04	5.18E-04	4.46E-04	2.00E-04	2.31E-04	-3.58E-04	5.44E-05		**0.292**	-0.016	0.061	0.004	-0.019	-0.003	-0.006
x	2	-0.025	1.02E-03	-1.80E-04	2.44E-04	4.85E-04	-2.64E-04	9.64E-05	8.87E-05		**0.085**	-0.011	-0.004	-0.003	-0.011	0.001	**-0.032**
x	3	-0.027	**2.63E-03**	3.51E-04	-1.97E-04	-5.44E-04	3.73E-04	1.50E-04	3.76E-04		-0.002	-0.028	-0.013	-0.021	0.000	**-0.040**	-0.017
x	4	**-0.045**	**2.67E-03**	1.50E-04	-7.41E-05	-1.19E-04	**5.06E-04**	-1.30E-04	-7.14E-05		-0.006	-0.020	-0.024	**-0.046**	0.006	0.002	0.003
t-stat	1	**-3.132**	1.125	0.955	1.078	0.594	0.795	-1.240	0.191		**5.050**	-0.342	1.983	0.136	-0.612	-0.140	-1.980
t-stat	2	-0.881	1.872	-0.478	0.835	1.765	-0.859	0.277	0.302		**2.052**	-0.447	-0.165	-0.168	-0.716	0.080	**-3.009**
t-stat	3	-1.075	**7.998**	1.153	-0.598	-1.827	1.322	0.573	1.310		-0.104	-1.712	-0.735	-1.146	0.032	**-2.289**	-1.523
t-stat	4	**-2.545**	**9.479**	0.601	-0.359	-0.462	**2.090**	-0.544	-0.319		-0.323	-1.500	-1.648	**-3.181**	0.446	0.179	0.332

Table 5 continued
Dealer Trade and Stock Return VAR, Subgroup Analysis

Panel B: Stock Quartiles by Dealer Gross Turnover (4=largest)

	Quartile	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6	TO
r	1	**-0.004**		**0.050**	0.022	0.014	-0.016	0.006	-0.032	2.171	-2.407	-1.706	**-3.297**	**-3.762**	-1.343	1.440	0.405
r	2	**-0.008**		0.006	0.034	0.028	-0.021	-0.018	-0.024	1.391	0.402	-0.909	-0.722	0.519	**-0.926**	-0.116	**2.781**
r	3	**-0.007**		0.007	0.025	0.016	-0.006	0.009	-0.009	**1.601**	**-0.876**	0.170	-0.549	-0.194	-0.070	-0.004	**3.360**
r	4	**-0.006**		-0.002	**0.042**	0.009	0.001	-0.002	-0.005	**1.588**	0.056	-0.028	-0.102	-0.150	0.068	-0.005	**3.264**
t-stat	1	**-2.080**		**2.088**	0.740	0.716	-0.656	0.260	-1.456	0.956	-1.231	-0.971	**-2.302**	**-2.355**	-1.205	1.156	1.442
t-stat	2	**-5.335**		0.328	1.766	1.767	-1.265	-1.090	-1.528	1.714	0.681	-1.600	-1.494	1.133	**-2.226**	-0.261	**5.326**
t-stat	3	**-6.103**		0.368	1.576	1.053	-0.380	0.626	-0.682	**3.491**	**-2.589**	0.497	-1.918	-0.686	-0.278	-0.017	**8.462**
t-stat	4	**-3.532**		-0.084	**2.206**	0.507	0.069	-0.136	-0.360	**9.008**	0.451	-0.232	-0.864	-1.189	0.576	-0.037	**8.697**
x	1	**-0.011**	5.47E-05	6.88E-05	3.45E-05	9.60E-06	2.08E-06	2.00E-05	4.45E-06		**0.154**	-0.003	0.020	-0.006	0.001	0.001	-0.002
x	2	**-0.035**	2.81E-04	-1.69E-04	-1.11E-05	-1.03E-04	-3.73E-05	4.43E-05	-6.91E-05		**0.125**	0.024	0.012	-0.002	0.007	0.009	**-0.012**
x	3	**-0.037**	**1.10E-03**	4.12E-04	1.09E-04	-2.50E-05	1.12E-04	1.46E-04	2.54E-04		**0.122**	**0.020**	**0.023**	0.010	0.003	0.000	**-0.016**
x	4	-0.016	**4.99E-03**	3.11E-04	5.94E-05	3.97E-05	**8.05E-04**	-8.00E-05	2.42E-04		0.036	-0.019	-0.009	-0.023	-0.002	-0.018	**-0.039**
t-stat	1	**-2.572**	0.965	1.246	0.910	0.261	0.060	0.439	0.119		**4.083**	-0.163	1.634	-0.685	0.139	0.289	-1.744
t-stat	2	**-4.058**	1.706	-1.212	-0.094	-0.979	-0.358	0.382	-0.607		**5.064**	1.927	1.591	-0.229	0.699	0.776	**-2.411**
t-stat	3	**-2.449**	**3.213**	1.579	0.534	-0.119	0.628	0.741	1.522		**6.380**	**2.004**	**2.571**	0.958	0.404	-0.053	**-2.310**
t-stat	4	-0.388	**8.570**	0.719	0.138	0.097	**2.174**	-0.201	0.656		1.918	-1.511	-0.768	-1.733	-0.205	-1.555	**-2.485**

Table 5 continued
Dealer Trade and Stock Return VAR, Subgroup Analysis

Panel C: Dealer Quartiles by Dollar Volume (4=largest)

	Quartile	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6	TO
r	1	**-0.003**		0.016	**0.054**	0.018	-0.006	0.005	-0.013	-0.682	-0.421	0.466	0.278	-0.692	0.349	-0.287	**1.046**
r	2	**-0.006**		-0.006	**0.037**	0.010	-0.003	-0.012	-0.018	-0.516	0.680	0.435	-0.060	0.115	0.246	0.545	**2.628**
r	3	**-0.005**		0.010	**0.038**	0.020	0.001	0.009	-0.013	**1.482**	-0.299	-0.204	-0.175	0.082	0.017	-0.289	**2.316**
r	4	**-0.006**		-0.001	**0.037**	0.012	0.003	0.006	-0.014	**1.765**	-0.250	-0.120	-0.251	-0.103	-0.128	0.037	**2.952**
t-stat	1	**-3.085**		0.883	**2.880**	1.117	-0.398	0.294	-0.915	-0.968	-0.740	1.000	0.465	-1.392	0.799	-0.750	**3.507**
t-stat	2	**-5.825**		-0.363	**2.021**	0.640	-0.166	-0.715	-1.202	-0.725	1.907	1.163	-0.164	0.276	0.657	1.522	**7.375**
t-stat	3	**-4.022**		0.634	**2.375**	1.335	0.049	0.665	-1.045	**4.365**	-1.082	-0.649	-0.742	0.279	0.073	-1.140	**4.604**
t-stat	4	**-5.701**		-0.030	**2.231**	0.836	0.195	0.426	-1.124	**8.927**	-1.358	-0.822	-1.727	-0.644	-0.878	0.252	**8.480**
x	1	**-0.005**	-9.94E-05	1.46E-04	7.41E-05	2.58E-04	2.65E-05	1.61E-04	1.16E-04		0.105	0.033	0.022	0.001	0.020	0.031	-0.004
x	2	0.004	-1.03E-04	**-2.39E-04**	3.44E-05	**-1.50E-04**	-2.58E-05	1.84E-06	2.74E-05		0.001	-0.048	-0.022	0.007	-0.003	0.008	**-0.014**
x	3	**-0.043**	**5.22E-04**	-5.56E-05	-5.24E-05	-1.38E-04	8.81E-05	1.27E-04	4.22E-05		**0.087**	0.009	**0.022**	-0.005	-0.013	-0.007	-0.004
x	4	-0.016	**2.00E-03**	4.21E-04	-3.64E-06	-2.10E-04	3.25E-04	-1.81E-04	1.62E-04		**0.057**	-0.014	-0.015	-0.022	0.006	**-0.030**	**-0.031**
t-stat	1	**-0.862**	-1.074	0.904	0.549	1.762	0.295	1.440	1.331		1.188	0.989	1.476	0.040	0.473	1.534	-1.732
t-stat	2	0.444	-0.664	**-3.022**	0.481	**-2.006**	-0.400	0.029	0.433		0.021	-1.377	-1.039	0.416	-0.135	0.779	**-3.020**
t-stat	3	**-5.871**	**4.202**	-0.456	-0.524	-1.315	0.871	1.356	0.502		**4.430**	0.742	**2.563**	-0.553	-1.518	-0.852	-1.144
t-stat	4	-1.102	**7.869**	1.978	-0.018	-1.304	1.899	-1.010	1.057		**2.481**	-0.914	-1.067	-1.348	0.534	**-2.205**	**-4.030**

Table 6
Components of Dealer Profits

The table reports details about dealer profits. Dollar profits are converted to weekly returns, based on the beginning-of-week inventory value. The total return to dealers is split into Information (Info), Market-Making (MM), and Mixed (Mix) components. See Section II for a more detailed description of return calculations. This procedure is done in aggregate and for stocks by size quartile (4=largest). Panel A reports unadjusted raw returns, while Panel B reports value-weighted index-adjusted returns. The value-weighted index for all stocks is the TAIEX index, while the value-weighted index for each stock quartile is the appropriate, computed quartile index. Returns are average weekly returns in percent. The inventory data begin in May 1997, so the sample includes only 239 weeks (trading data begin in January 1997 and includes 261 weeks). **Bold** indicates statistical significance, i.e. |t-statistic| ≥ 2, and t-statistics are placed below returns.

Panel A: Unadjusted Returns

	N	Total	Info	MM	Mix	Index
Aggregate	239	0.307%	0.258%	0.004%	0.023%	-0.072%
		1.035	1.017	0.536	0.449	-0.254
Quartile 1	239	**-0.866%**	**-0.883%**	0.006%	0.063%	**-0.922%**
		-2.925	**-3.075**	1.304	1.841	**-3.359**
Quartile 2	239	-0.166%	-0.232%	**0.020%**	**0.088%**	-0.503%
		-0.582	-0.869	**4.353**	**2.818**	-1.651
Quartile 3	239	0.048%	-0.054%	**0.033%**	0.091%	-0.346%
		0.160	-0.199	**5.603**	2.303	-1.160
Quartile 4	239	0.506%	0.461%	-0.004%	0.009%	0.049%
		1.610	1.751	-0.389	0.141	0.167

Panel B: Index-Adjusted Returns

	N	Total	Info	MM	Mix
Aggregate	239	**0.378%**	**0.329%**	0.076%	0.095%
		4.828	**4.249**	0.271	0.397
Quartile 1	239	0.057%	0.039%	**0.928%**	**0.985%**
		0.443	0.307	**3.388**	**3.835**
Quartile 2	239	**0.337%**	**0.271%**	0.522%	**0.591%**
		3.775	**2.845**	1.724	**2.099**
Quartile 3	239	**0.394%**	**0.292%**	0.379%	0.437%
		5.638	**4.057**	1.282	1.630
Quartile 4	239	**0.458%**	**0.412%**	-0.052%	-0.040%
		5.423	**5.092**	-0.182	-0.166

Table 7

Higher Moments: Volatility and Kurtosis

This table reports the relation between dealer trading and higher moments of volatility and kurtosis. For each month, we calculate volatility and kurtosis of daily returns as well as average daily gross dealer trading volume (both turnover and dollar volume) for each stock. Regression specifications are shown in each panel. We implement the regressions as in Fama and MacBeth (1973) with cross-sectional regressions in each time period and weighted (by degrees of freedom) time-series parameter estimates and t-statistics. All results are statistically significant.

Panel A: Stdev = βDealerTO + ε

Weighted Measure	N	Intercept	β
Mean	66	0.028	3.904
t-stat	66	41.165	12.620

Panel B: Stdev = βDealerAmount + ε

Weighted Measure	N	Intercept	β
Mean	66	0.029	4.888E-11
t-stat	66	41.760	5.517

Panel C: Kurtosis = βDealerTO + ε

Weighted Measure	N	Intercept	β
Mean	66	0.481	-479.721
t-stat	66	8.573	-11.954

Panel D: Kurtosis = βDealerAmount + ε

Weighted Measure	N	Intercept	β
Mean	66	0.402	-8.297E-09
t-stat	66	7.138	-8.329

Table 8
Contemporaneous Correlation of Dealer Trades

The table reports cross-sectional dealer trade correlation based on the herding measure from Lakonishok, Shleifer, and Vishny (1992):

$$H(i,t) = \left| \frac{B(i,t)}{B(i,t)+S(i,t)} - p(t) \right| - AF(i,t)$$

B(i, t) and *S(i, t)* are the numbers of buyers and sellers, *p(t)* is the expected proportion of buyers in the current time period, and *AF(i, t)* is an adjustment factor equal to the expected value of the first term (inside absolute value bars) given the null of no herding and a binomial distribution of *B(i, t)* vs. *S(i, t)*, with probability of *B(i, t)* equal to *p(t)*. "Modified" uses $p(t) = 0.5$ to reflect a null hypothesis that if there is no herding then half of dealers will buy and sell a given security in a given time period. "LSV" uses $p(t)$ as the proportion of buyers across all stocks and all dealers in time period t (see the Hypotheses section for details). Q1 to Q4 are size quartiles (Q4=largest).

	N	Modified	Modified t-stat	LSV	LSV t-stat
Aggregate	41365	2.24%	24.13	1.33%	15.81
Quartile 1	3021	5.60%	13.55	4.65%	12.39
Quartile 2	4942	2.57%	8.23	1.87%	6.59
Quartile 3	10351	1.26%	6.31	0.98%	5.37
Quartile 4	22945	2.15%	19.49	0.92%	9.28