Who Makes Markets?
The Role of Dealers and Liquidity Provision

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First Draft: 1.20.2003
Current Draft: 1.25.2004

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 making, such as Kyle (1985) and Grossman and Miller (1988), 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. We also develop a unique profit decomposition to compare intraweek information and market making profits. Dealers earn significant excess returns, in aggregate driven by information rather than market making. Subgroup analysis reveals that information profits are positive and increasing in stock capitalization, and market making returns are positive and significant for all but the largest stocks.

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Dealers in most financial markets are proprietary traders who are assumed to provide liquidity, and therefore they are granted 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, and the right to bypass brokers, which allows for lower transaction costs and faster trade execution. These advantages allow dealers to trade quickly, efficiently, and at low cost relative to the rest of the market. In return for these trading advantages, dealers are expected to perform the socially beneficial and profitable function of supplying liquidity.

In general, when liquidity providers trade, 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 competitive 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 of these models, other market participants push the price up (down) when they buy (sell), while 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 contemporaneous relation.

In this paper, we examine whether the typical advantages granted to dealers induce them to act as liquidity providers. The Taiwan Stock Exchange (TSE) grants dealers a direct connection to the electronic exchange trading mechanism, which in turn allows them to avoid otherwise mandatory broker fees and trading delays. Thus, TSE Dealers have smaller marginal trading costs, higher transaction speed, and closer access to the market than other investors in the TSE; in effect the same advantages granted to other dealers across the world. However, unlike some others, TSE Dealers are not constrained to provide two-sided quotes or "stable and orderly" markets; they have a free market decision whether or not to provide liquidity. It is important to note that liquidity provision in the Grossman and Miller model is also a free market provision; dealers willingly provide liquidity in return for the expected profits from transacting at a spread from fair value. By studying unconstrained TSE Dealers, we gain insight about whether these advantages naturally induce liquidity provision.

Contrary to policy motivation and model intuition, our two main findings both suggest that dealer advantages do not induce liquidity provision. First, the contemporaneous correlation between weekly dealer order flow and stock returns is strongly positive, implying that dealers do not provide liquidity at a weekly frequency. Second, using detailed intraweek transaction price and quantity data, we develop a unique method to decompose dealer profits. [1] We find that dealers earn significant excess returns that are driven by information profits rather than market making profits. The information-driven returns reinforce the main result by showing that dealers do little to provide liquidity within the week. The small magnitude of market making profits relative to information profits suggests that either dealers actively choose not to provide liquidity or that liquidity provision is not a highly profitable activity.

Our results are particularly surprising because dealer advantages give a great comparative advantage for high-turnover trading strategies. While long-term investors may *desire* such privileges, market makers *require* them to profit from the high-frequency trading nature of liquidity provision. However, we find that instead of inducing market-making behavior, these trading advantages enable dealers to be super-efficient information traders. Dealer activities, such as focusing on order flow information, may enable them to deduce material pricing information. Low transaction costs and high transaction speeds may allow them to take advantage of such information-driven opportunities that would not otherwise be profitable. Thus, assuming that

[1] Detailed definitions of information profits and market making profits are in Section II.

dealers want to maximize profits, their privileges may very well induce information as the primary motive for trade.

In most models of dealer trades, dealer roles and profits are analyzed assuming that they trade primarily as market makers. Given this fundamental 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[2] for each trade. Madhavan and Smidt (1993) develop a model that includes target inventory levels, information asymmetry, and liquidity provision as motives for dealer trading. In spirit, their model incorporates the idea that dealers may strategically trade on information. Still, their model implies a negative relation between dealer order flow and returns, which is consistent with trading primarily for market making motives. Empirical research about dealer trades also typically takes as given that dealers are market makers and analyze the data as such. These studies, including Ho and Macris (1984), Glosten and Harris (1988), Hasbrouck (1991), and many others, typically focus on high-frequency datasets and phenomena. They often have data for relatively few dealers and short time periods. Appropriately, the valuable contributions that these studies make are regarding issues that are not likely to be affected by the limited data, such as determining components of the bid-ask spread, analyzing price-discreteness effects, and disentangling high-frequency information and inventory motives for trade.

To the best of our knowledge, our paper is the first to study whether the institutional advantages granted to dealers impart the incentive to provide liquidity. We use a unique and comprehensive dataset of dealer trades, transaction prices, and inventory, over a five-year horizon. We aggregate

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

trades across all dealers in the market to lessen effects of individual dealer idiosyncrasies, and we use over five years of data to mitigate period-specific relations.

Section I describes the dataset and market in detail, Section II defines the hypotheses and corresponding empirical tests, Section III documents the test results, and Section IV concludes with a brief summary, institutional implications, and directions for future research.

I. Data and Markets

A. Database

We use the Taiwan Economic Journal (TEJ) database of equities traded on the Taiwan Stock Exchange 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 I and then describe the institutional setup of the TSE.[3]

INSERT TABLE I

Table I illustrates the clear pattern that large capitalization 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

[3] 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), the TSEC Annual Report (2002), and a conversation with an anonymous TSE representative.

see the pattern that smaller stocks had larger autocorrelations at almost all lags. Given the time period of 255 weeks, or the full 261 weeks less 6 weeks to create lags (implying a standard error of autocorrelation estimates of roughly 0.063), there are several statistically significant values for lag 1 through lag 3 autocorrelations in smaller stocks.

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, so it is not as susceptible to price manipulation as typical emerging markets may be.

B. 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 approximately 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[4] 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 TSE platform under the same trading rules. Listed stocks meet more stringent stability and size requirements, and the value-weighted performance of listed stocks determines the TAIEX index. TSE stock trading is restricted to occur only on the TSE 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). In practice, most OTC stock trades still take place on the TSE platform. Our data do include all trades executed on the TSE system (all TSE stock trades and most OTC stock trades). Trade data are collected and recorded by Taiwan's Securities and Futures Commission (SFC) and reported to the TEJ, insuring completeness and reliability.

C. TSE Dealers

Only two types of institutions may submit trades directly to the TSE trade execution system: TSE Brokers and TSE Dealers. All other individual and institutional trades must be submitted through TSE Brokers. Brokers have access to the TSE 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.

TSE Dealers are institutions that trade 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

[4] 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.

US$350 thousand) must be left in an interest-bearing account as a security deposit. Dealer access to the TSE is for own-account trading purposes only, and their namesake portrays the SFC's desired role for them as liquidity-providing market makers. In Taiwan Securities & Futures Markets (2003), the SFC states that, "By conducting proprietary trading, the (TSE) dealers increase market liquidity and help to stabilize the market." However, they have no explicit mandate to provide two-sided quotes in any security, and they are free to choose which securities to trade in. Since they are afforded access to the TSE system and are explicitly forbidden to trade on insider information, their trade data are readily available. See Table II for summary statistics about TSE Dealer trades and Figure 1 for Dealer trading dollar volume percentiles.

INSERT TABLE II and FIGURE 1

As shown in Table II, 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[5], which decays rapidly. Average weekly net turnover was -0.009%, implying that dealers generally sold a little 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. TSE Dealers accounted for roughly 2% of total share trading volume[6]. This guarantees that they are not the only source of liquidity, if they are in fact providing liquidity. Figure 1 illustrates the cross-sectional difference in dealer trading activity, plotting dollar volume at the 10%, 50%, and 90% levels.

[5] 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].
[6] From 1997 to 2001, TSE Dealer trades accounted for only 1.37% to 1.94% of total dollar trading volume.

D. Dealer Transaction Speed and Cost Advantages

Only TSE Brokers and Dealers have direct connections to the TSE computer trade execution system, and they can enter trades as fast as they can key them in (they are allowed multiple trade terminals). They also receive detailed transaction reports instantly upon trade execution. All other traders have to trade through Brokers as an intermediary. Internet trading was not widely available (well under 1% of the volume traded consisted of internet orders over the sample period), and even where available brokers were forced to manually print and key in internet orders. Hence, the actions required for a typical individual or institutional 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 TSE 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, TSE 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.

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.[7] Since Dealers do not have to trade through brokers, they avoid this brokerage cost. Given the minimum tick price grid is about 10-20 basis points for over 75% of stocks, a trading discount of 28.5 basis points relative to other market participants puts TSE Dealers at a huge advantage for high turnover trading strategies. However, this advantage is clearly not critical for long-term investors: saving 28.5 basis points on a position held for a year or more is marginally meaningful at best, and such meager savings would require a huge investment

[7] Internet trading costs ranged from 20 – 28.5 basis points round trip. Less than 1% of trading volume was through internet orders over the sample period.

to justify the costs of maintaining TSE Dealer status. Seppi (1997) models dealer trading advantages as discounted trading and instant execution ability. TSE Dealers advantages are almost identical to Seppi's theoretical advantages, so in theory they should enable dealers to profit from liquidity provision.

E. 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.

F. 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 they 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.

II. Hypotheses

A. 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 market maker 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 traders 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 $x + u$, further 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 consider market maker 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 imply the same negative contemporaneous relation between market maker trades and security returns.

Our primary test of the contemporaneous correlation is a modified vector auto-regression (VAR) of dealer order flow and stock returns. In a typical VAR, only lagged variables are included as independent variables, but we include the contemporaneous dealer order flow as an independent variable in the return regression (and vice versa) since this is precisely the relation we are interested in.[8] Dealer order flow drives contemporaneous returns, and this is the justification for including contemporaneous order flow as an independent variable in the return regression. However, since we use weekly data for our tests, it is possible that causality also exists in reverse direction (returns may drive contemporaneous dealer order flow if there are trade motives other than liquidity provision, such as intraweek momentum trading), so we include the other contemporaneous variable in both the return and order flow regressions.[9] We focus our discussion on the return regression because the causality in that case is driven by liquidity provision, whereas the reverse causality would be driven by alternative null hypotheses (momentum trading, etc.). By using the VAR, we can measure the contemporaneous correlation while controlling for up to six-week momentum or contrarian effects and delayed price impact of dealer trades and gain insights about such predictive relations. 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 raw returns, index-adjusted returns, and size-quartile-index adjusted returns for robustness.[10] 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

[8] Since our modified VAR is not correct in a strict econometric sense, we do the following robustness check. We calculate the correlation of the residuals from a standard VAR (including only lagged dependent variables as independent variables). All results are qualitatively identical to our modified VAR results.

[9] See Hasbrouck (1991) for a clear discussion of a VAR of order flow and returns, particularly for including contemporaneous order flow as an independent variable in the return regression.

[10] In preliminary tests, we did not find significant return patterns across book/market ratios or market beta, hence we do not consider these potential risk factors in our return adjustments. Furthermore, momentum of up to six weeks is already effectively controlled for in the lagged return independent variables.

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 consensus method to determine the "correct" number of lags to include in such a regression. We include six lags (enough to study and correct for predictive relations of up to six weeks), which we feel is enough given our summary statistics that autocorrelation does not exist in either returns or order flow beyond three weeks.

In the context of our VAR 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.

B. 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. This dollar decomposition is similar to that in Ellis, Michaely, and O'Hara (2000) and (2002), except that we separate the mixed profits from information profits. After calculating the dollar profits from each stock in a single period, we sum the profits across stocks and dealers. The initial base for conversion to return is the inventory value of all dealer holdings at the beginning of the week. This base maintains the relative importance of each component and allows us to sum the components to calculate total weekly return. In other words, the total dollar profit is the sum of the dollar profit components, and the total return is the sum of the return components.

Finally, we convert the market making and information dollar profits to returns based on dollars employed for each individual purpose. The market making base is the average between the buy and sell value of stocks traded within the week, and the information base is the beginning-of-week value of stocks held for the entire week. Although returns calculated with these bases no longer sum to the total weekly return, this return conversion is more appropriate to understand the individual component returns. These base values represent capital employed for market making and information, respectively, instead of total value of inventory. 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.

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.

$$\prod = [InformationComponent] + [MarketMakingComponent] + [MixedComponent] \tag{3}$$

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

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

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*; *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. 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 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. Since it is impossible to identify whether they traded for information or market making motives, we differentiate these profits from the first two categories.

C. 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

[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.

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 our suggestive way until better tests are devised.

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

If dealers are performing the function of providing liquidity, then their relative volume (dealer volume / total market volume) should be higher 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 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 relative dealer trade activity during periods of higher volatility and kurtosis.

For each stock in each month (indexed by *t*), we calculate volatility and kurtosis of daily returns as well as daily dealer trading volume divided by total market volume. The following are the simple regression specifications:

$$(dealervolume_t / marketvolume_t) = \alpha + \beta volatility_t + \varepsilon_t \tag{6}$$

$$(dealervolume_t / marketvolume_t) = \alpha + \beta kurtosis_t + \varepsilon_t \tag{7}$$

$$(dealervolume_t / marketvolume_t) = \alpha + \beta_1 volatility_t + \beta_2 kurtosis_t + \varepsilon_t \tag{8}$$

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 average parameter estimates and t-statistics. Our null hypothesis implies positive values of β, β_1, and β_2.

E. 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).

[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.

$$H(i,t) = \left| \frac{B(i,t)}{B(i,t) + S(i,t)} - p(t) \right| - AF(i,t) \tag{9}$$

$B(i, t)$ 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 capital inflows to the investment 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 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

[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.

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.

III. Empirical Results

We briefly summarize the primary empirical results, followed by a more detailed description of the tests and results. Our first major 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, driven by their information trades. This suggests that the advantages dealers are afforded in transaction speed and information access are advantageous in an economically significant way. These intraweek results support the initial finding.

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

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 weighted Fama and MacBeth (1973) style cross-sectional regressions with time-series significance tests. We test variations of the basic VAR, using only TSE stocks, TSE plus OTC stocks, controlling for

[14] As mentioned in Section II, we also calculated the correlation of residuals from a standard VAR with only lagged variables. The pooled correlation coefficient was 0.056 (t-statistic 16.6) and the Fama and Macbeth (1973) style correlation was 0.067 (t-statistic 10.4). T-statistics from simple correlations of returns and order flow and univariate regressions range from 6.10 to 9.53.

overall market turnover, and not controlling for overall market turnover. Wang (1994) shows that overall market turnover and stock returns should have a strong relation, and we confirm this in our data. As a robustness check, we also run pooled regressions and bootstraps to estimate standard errors[15] for each variation. These results are qualitatively identical.

INSERT TABLE III

The t-statistics for the contemporaneous relation between return and dealer net turnover range from 8.53 to 9.91 in the return regressions and from 6.28 to 8.43 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, since OTC stocks are omitted to eliminate potential off-exchange price effects[16] and overall market turnover is included as a control variable. In the return regression of *Panel D*, contemporaneous dealer order flow is both economically and statistically significant, with a coefficient of 2.025 and a t-statistic of 9.91. 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 2.025%. 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.[17]

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[15] First, we randomly chose 255 time periods (our trade data includes 261 periods, and we needed the first six to create lags) 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.
[16] All subsequent results use only listed stocks, unless otherwise specified.
[17] In the rest of this section, we continue to focus on Panel D unless otherwise stated.

One potential argument against the result is that perhaps dealers are simply block traders that have a mechanical price impact when they trade. Holthausen, Leftwich, and Mayers (1987) find an analogous 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).[18] Our results only include what they would define as permanent weekly effects. Holthausen et. al. show that price impact is detectable on a tick-by-tick basis, but is dramatically reduced by the end of the trading day. Extrapolating from this result, permanent weekly price impact should be almost nonexistent. Our permanent weekly contemporaneous price effect dwarfs 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.

B. Test 1: Causality and Higher Frequency Implications

Since we have only weekly dealer trade data, the positive contemporaneous relation is conclusive evidence only that dealers do not provide liquidity on a weekly basis. However, we do 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 the return regression, the coefficient of lag 1 order flow is 0.033 with a t-statistic of 0.18. 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).

[18] 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.

The coefficient of lag 1 return on the order flow regression is 1.37×10^{-4} with a t-statistic of 1.57. This indicates that return from the previous week also has no 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.

C. Test 1: Other Noteworthy Effects

Other significant findings illustrated in the VAR are positive return autocorrelations, evidence of momentum trading, inventory decay, and the overall market turnover control variable. First, return autocorrelation coefficients for lag 1 – lag 3 returns are positive. The effect is stronger in the OTC stocks because they are smaller in capitalization. This confirms that the positive weekly autocorrelations and pattern across size shown in the summary statistics still hold after correcting for dealer order flow and market turnover. Second, there seems to be some weekly momentum trading by dealers. In the order flow regression, coefficients on lag 1 to lag 6 returns are all positive, and the coefficient on lag 4 return is significantly positive. This indicates that dealers may be following a monthly momentum trading strategy. Third, dealers continue to build up inventory after the first week and then slowly sell out of the position. In the order flow regression, the lag 2 to lag 6 autocorrelation coefficients are all negative. In fact, in separate tests we found that the order flow autocorrelation coefficients are universally negative from lag 2 to lag 15, indicating that dealers continue trading out of new positions over 15 weeks or longer. Finally, the overall market turnover control variable has effects in both the return and turnover regressions, though it does not affect the other coefficients. In the return regression, the t-statistic on turnover is 6.41 implying that higher turnover is associated with higher excess return. On the dealer order flow regression, the t-statistic for overall market turnover is -2.95, 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 increase inventory to provide liquidity during periods of high market turnover. Instead, this is additional evidence that dealers do not provide liquidity.

INSERT TABLE IV

Table IV shows the same VAR specification, this time in the more typical form without contemporaneous variables. This table illustrates that the secondary effects described above also hold in the traditional VAR framework.

D. Test 1: Subgroup Analysis and Patterns

We estimate three subgroup variations of the basic VAR to further explore the main result. Because some quartiles had few observations per period, we report the results from pooled regressions with bootstrapped standard errors. Again, the t-statistics from Fama and MacBeth (1973) style regressions are qualitatively identical, though some the coefficients vary wildly in some panels due to the mentioned issue. See Table Va below for results.

INSERT TABLE V

First, we sort stocks by size quartiles at the beginning of the previous year and test each of these size quartiles.[19] In *Panel A*, we see that the coefficient for contemporaneous turnover, *x0*, is positive and generally increasing in stock size. The t-statistics are all increasing in stock size, from relatively insignificant to strongly significant. 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. Additionally, it seems that dealers trade out of positions in large capitalization stocks more aggressively.

In the second subgroup, we examine dealer participation directly by sorting stocks by dealer gross turnover in the previous year,[20] 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. We also find a curious pattern for stocks that dealers do not trade often. For such stocks (quartile 1), the predictive return effect of dealer trade over the next 5 weeks is extremely negative.

In the third and final subgroup shown in *Panel C*, we sort dealers by dollar volume in the previous year. In other words, we sort dealers by how actively they traded in the previous year. The pattern across the coefficient for *x0* shows that large, active dealers have a larger positive contemporaneous price effect than small, inactive dealers. The negative coefficients for quartiles 1 (smallest) and 2 are consistent with models of liquidity provision, though neither coefficient is statistically significant. We also find evidence of negative predictive effects of dealer order flow for active dealers (negative coefficients on the lagged order flow coefficients of the return regression), as well as positive feedback trading.

E. Test 2: Dealers Earn Excess Returns

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[19] In Panel A only we adjust returns by appropriate value-weighted size quartile returns instead of the aggregate value-weighted index, because of the significant size effect found in the summary statistics.
[20] 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.

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

INSERT TABLE VI

Panel A reports the average weekly dollar profits to dealers, both in aggregate and across stock capitalization quartiles. Total weekly profits are about NT$131 million, and it seems that profits from the largest stocks subsidize losses in the smaller stocks. In particular, information profits in the largest quartile of stocks drives the entire result. Market making profits are positive for quartiles 1 – 3 (and significant for quartiles 2 and 3), but negative for quartile 4. Though liquidity provision can provide statistically significant profits for some stocks, the tiny magnitude of positive market making profits (excluding quartile 4) suggests that there are simply very little rents to liquidity provision.

Panel B simply reports the return to each component in *Panel A*, where the base for the return calculation is the beginning-of-week inventory value in each period. This allows comparison of profitability from each component relative to the total capital of the dealers. Average unadjusted weekly returns for dealers is 28.4 basis points (about 14.76% annually) with a t-statistic of 0.94, over a period that the value-weighted index average return was -7.2 basis points weekly (about -3.74% annually).

Panel C reports risk-adjusted returns to the information and market making component of returns. The bases for return conversion of the information profits and market making profits are the dollars employed for information trades and market making trades, respectively. Additionally, we adjust the information return for the appropriate value-weighted aggregate or quartile index return in each period.[21] We do not adjust the market making return because the risk benchmark for market making profits is not clear; in fact zero might be the appropriate benchmark. In addition, market making profits are from positions opened and closed in the same week. Since dealers may open a position either by buying or selling, it is unclear whether they start by buying or selling and hence whether they are long or short for part of the week. "Info-Index" denotes the risk-adjusted information returns, and "MM" denotes market making returns. Information returns are positive in aggregate and for each quartile. They are increasing in stock size and statistically significant for quartiles 2 to 4. Market making profits are negative in aggregate, but they are positive and statistically significant for quartiles 1 to 3 and negative and statistically significant for quartile 4. They are decreasing from quartiles 2 to 4, and we conjecture that they are indeed greatest for quartile 1. However, due to infrequent trading of the smallest stocks, dealers often cannot close out positions opened for market making reasons in the same week. Finally, *Panel C* illustrates that dealers outperform the appropriate risk benchmark across the board, in each profit component of each stock size quartile.

Regarding the magnitude of the information profitability, it is well-documented that mutual funds (and other institutions) in the US and internationally significantly outperform their benchmark indices before fees. Since we do not have access to costs associated with being dealers, we cannot adjust for such costs. We can only recognize that the extreme excess returns are not quite as high as they seem in our analysis. For that matter, it is also unclear whether the fees should be deducted from information or market making returns.

F. Test 3: Dealers Infer Relevant Pricing Information

[21] In principle, we would instead adjust for market beta or other systematic factors, but in preliminary tests we found that return patterns across beta and book to market are weak. However, return patterns across size are clear and striking, hence we adjust for size quartile returns as described.

Test 1 is inconclusive with respect to whether dealers infer material pricing information, and *Test 2* is suggestive that they do. Hence we neither confirm nor reject *Hypothesis 3*. Based on the VAR used to test *Hypothesis 1*, we see a strong contemporaneous price effect of dealer order flow, but little evidence of predictive effects. However, in the subgroup analysis of Table Vc, we see that the most active dealers have a strong positive contemporaneous price effect followed by a possible reversal effect. The magnitude of the reversal is about 50% of the initial price effect. This indicates that the most active dealers may overtrade on what information they have, potentially taking advantage of positive-feedback strategies. Other panels in the subgroup tests also show significant predictive effects, indicating potential strategic trading. Based on *Test 2*, dealers are indeed profitable, and their profits are driven by the information component rather than the transaction (market making) component. Although we cannot determine whether their information profits are driven by inside information, superior trading models, or inferred information, the magnitude of the profits is highly suggestive that dealers somehow infer material pricing information from their focus on order flow information.

G. 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. We find inconclusive evidence and can neither confirm nor reject *Hypothesis 4*. Relative dealer volume is decreasing in return volatility and increasing in return kurtosis.

INSERT TABLE VII

In *Panel A* of Table VII, we report the results of regressing relative dealer volume on standard deviation of daily returns. Using standard deviation as the independent variable, we find a coefficient of -0.524. On average, if return volatility is 1% higher during a given month then [dealer volume] / [market volume] will decrease by 0.524%. The t-statistic of -4.10 indicates a statistically significant relation. In *Panel B*, we observe that dealer turnover is positively related to kurtosis. The interpretation of the coefficient of 0.003 is similar, and the t-statistic of 4.46 again indicates high statistical significance. *Panel C* shows similar relations using both standard deviation and kurtosis as independent variables. While the coefficients and t-statistics have decreased in magnitude, they are still significant and in the same direction as the univariate results.

These results indicate that dealer relative trading volume is lower when volatility is higher, but higher during extreme price movements. In additional tests, we find that the opposite relations hold when regressing absolute (instead of relative) dealer volume on the higher moments. Dealers trade more during volatile periods and less during kurtotic periods, but the rest of the market trades even more during volatile periods and even less during highly kurtotic periods. These results show that dealer relative trade may in fact be higher when the market needs it (highly kurtotic periods), but not necessarily during periods of high volatility.

H. 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 VIII, 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 VIII

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 might imply a measure of 50% instead. Therefore, the initial interpretation of the LSV measure underestimates actual herding in some cases.

We use the LSV measure 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.

IV. Conclusion

We have shown that in aggregate, dealers do not provide liquidity to the market; instead, they trade on information. First, the contemporaneous correlation between dealer order flow and stock returns is highly positive, inconsistent with models of market maker trades. 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. Next, we explored higher moments of stock returns to gain further insight into when dealers trade. Relative dealer volume is inversely related to volatility and positively related to kurtosis. Finally, we justified our aggregation of dealer trades by establishing a significant contemporaneous correlation across individual dealer order flow.

The contemporaneous correlation and information profit results across stock size are consistent with the following theory. 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 few and therefore easily detectable and effectively restricted from releasing the information via insider trading. Since there is little insider trading in small firms, it is difficult for market makers to extract information from order flow and earn information profits in small firms. For large firms, it is easier for informed traders to trade without being detected by regulators. Since informed traders are more willing to actively trade large firms' stocks, dealers will be able to infer more information from order flow.

The market making profit pattern across stock size also has an intuitive interpretation. Large-cap stocks are more liquid than small-cap stocks by many measures (higher volume, lower bid-ask spreads, etc.), likely because there is a much larger, active investor base. When there are perceivable order imbalances in large-cap firms, there are more potential agents competing to absorb the imbalance. Since the natural liquidity is higher for larger stocks, dealer liquidity provision for large firms does not have the same profit potential as for small firms; dealers must compete with other de facto dealers as well as natural liquidity. The implication of both of these theories is that dealers may be necessary only for small or illiquid stocks.

A. Institutional and Policy Implications

The recent controversy at the New York Stock Exchange (NYSE) highlights the regulatory attention given to liquidity provision. Our results suggest that granting a set of institutional trading advantages to a class of investors and naming them "dealers" does not necessarily promote liquidity provision for other participants (though it may increase total trading volume). Although we find that market making can be profitable for small stocks, the small magnitude of the profits indicates that institutional incentives can do little to increase liquidity provision, short of mandating dealers to set narrowly placed bid and ask quotes at large depths. Given such a liquidity mandate, it is unlikely that any institution would want to be a dealer unless liquidity provision activities are subsidized by advantages in other areas. The subsidization of dealer profits and the social benefit of liquidity provision for those demanding immediacy are presumably funded at the expense of either "noise traders" or long-term investors, via large information profitability of dealers.

Our findings from studying unconstrained dealers also indicate that there is a large shadow cost to liquidity mandates. Therefore, it is natural that dealers with such mandates will try to strategically minimize this cost. Two prominent examples of such strategic minimization of liquidity provision responsibilities are the 1997 NASDAQ price-fixing scandal and the current scrutiny on NYSE Specialists. NASDAQ dealers were accused of collusion via large price ticks and for transacting against naturally crossing trades to "steal the spread." Recently, NYSE Specialists have also been accused of stealing the spread by blocking incoming trades temporarily, in addition to not employing enough capital aggressively toward liquidity provision. In general, granting trading advantages to dealers and requiring them to provide liquidity in return leaves natural incentives to maximize their advantages and minimize their costs. Hence, strategic trading by dealers will continue to whatever extent is allowed or undetectable by regulators.

In the final analysis, the advantages afforded to dealers should be commensurate with the risks they take and the social benefit they provide through liquidity provision. If they cannot provide this service, then the market should be left to provide liquidity for itself. In particular, our evidence that dealers profit from information in large-cap stocks indicates that dealers are not necessary to ensure ample liquidity provision in these stocks. Since dealers can profit from making markets in smaller, less liquid stocks, they may still play a valuable role in these stocks. These takeaways are consistent with anecdotal evidence from two former NYSE Specialists about the lack of market making profits in large stocks, as well as the Euronext market (Amsterdam, Brussels, Lisbon, Paris) policy of having dedicated liquidity providers for all but the largest stocks. Accordingly, other regulators should also consider whether the advantages given to dealers impart the incentive to provide liquidity at a reasonable cost, particularly for large and liquid stocks.

B. 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 provide little liquidity within the week as well. However, conclusive statements about higher frequency liquidity provision can only be made with higher-frequency data, and we hope to test this upon availability. Furthermore, this paper focuses on aggregate dealer trading and behavior to establish that dealers are generally not liquidity providers. In ongoing research, we further explore cross-sectional trading patterns across dealers to understand what drives differences in profitability across dealers, given the premise that they may not be liquidity providers.

On a final note, the profit decomposition and return conversion illustrated in this paper have other natural applications. One example is for mutual fund manager evaluations. Given detailed transaction price and holdings data, our profit decomposition and return conversions can be applied at different frequencies (monthly, quarterly, annually) to differentiate fund managers' long-term stock-picking ability from intra-period trading ability. Since our information returns are based on stocks held for an entire period, standard risk benchmarking to determine risk-adjusted performance (alpha) is applicable. However, current mutual fund evaluations do not take into account that trading profits should have a different risk benchmark. By separating trading and information returns, we can choose appropriate benchmarks for each, instead of applying a single benchmark to total return. Another example is in studies of liquidity and security return patterns, such as the hypothesized liquidity premium. Just as size, bid-ask spreads, and market turnover proxy for liquidity, so does dealer market making profitability. The ability for dealers to make large market making profits indicates a low level of natural liquidity, and vice versa. Given the availability of appropriate data, securities can be sorted by our definition of dealer market making profits, and this sorting can be used to test differences in return patterns across securities with different levels of natural liquidity.

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TABLES AND FIGURES

Table I. 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	485	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 II. TSE Dealer Trading Summary Information

The table reports summary information about TSE 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 order flow, first pooled across all listed and OTC stocks followed by cross-sectional mean and standard deviation. *Panel C* reports Fama and MacBeth (1973) style aggregate dealer trading statistics (except for the number of stocks traded, which is per dealer per week). 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 Order Flow

	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
Mean Number of Stocks Traded	261	47.24	1.09	5.10	96.36
StDev Number of Stocks Traded	261	36.88	0.95	3.91	69.29
Skew Number of Stocks Traded	261	1.31	0.03	0.61	3.29

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

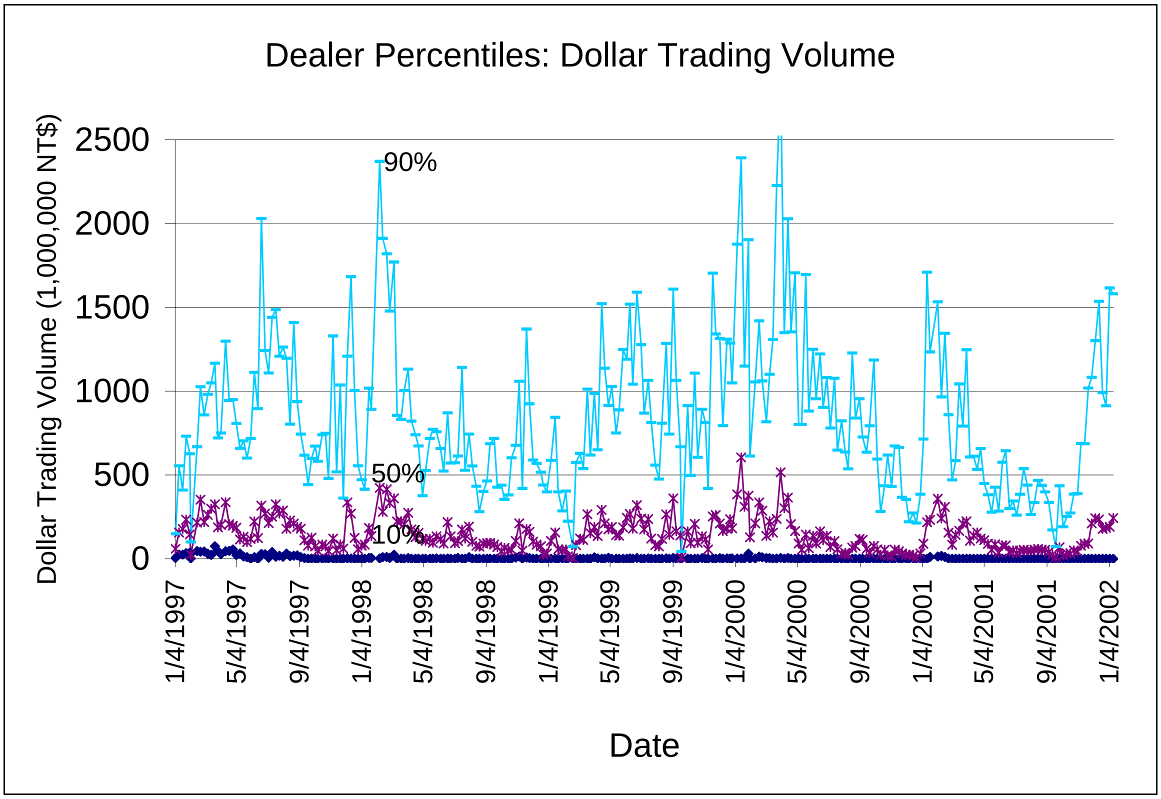

Table III. Dealer Order Flow and Stock Return VAR

This table reports weighted Fama-MacBeth (1973) style regression results for the following VAR specification:

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

r is weekly stock return (excess over the value-weighted index), *x* is weekly aggregate dealer net order flow (net trade / shares outstanding), and *TO* is overall market turnover. *Panels A* and *B* include listed (TSE) and over-the-counter (OTC) stocks, while *Panels C* and *D* include only 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 order flow regressions), and x0 – x6 refer to the regression coefficients on independent dealer order flow variables (B_0-B_6 for the return regressions and D_1-$D_6$for the order flow regressions). **Bold** indicates |t-statistic| ≥ 2. Boxed indicates a group of lagged variable coefficients with consistent signs, which may indicate significant relations.

Panel A: TSE+OTC

	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6
r	-0.001		**0.038**	**0.034**	0.016	0.005	-0.011	-0.011	**1.686**	-0.151	0.151	0.022	-0.222	-0.058	0.102
t-stat	-0.91		**3.22**	**3.15**	1.81	0.51	-1.28	-1.22	**8.53**	-0.96	0.97	0.15	-1.50	-0.44	0.65
x	0.000	**2.07E-03**	2.08E-04	1.07E-04	8.67E-05	**4.64E-04**	1.13E-04	-1.71E-05		**0.074**	-0.010	-0.013	-0.013	-0.005	**-0.026**
t-stat	-1.40	**6.28**	0.95	0.52	0.40	**2.24**	0.51	-0.09		**4.94**	-0.92	-1.27	-1.12	-0.32	**-2.42**

Panel B: TSE+OTC, Control TO

	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6	TO
r	**-0.005**		**0.026**	**0.026**	0.014	0.005	-0.013	-0.010	**1.659**	-0.178	0.161	-0.020	-0.213	-0.093	0.075	**1.981**
t-stat	**-4.75**		**2.30**	**2.56**	1.56	0.54	-1.52	-1.19	**8.65**	-1.03	1.10	-0.14	-1.51	-0.69	0.50	**6.06**
x	0.000	**2.16E-03**	1.66E-04	7.47E-05	7.88E-05	**4.53E-04**	1.46E-04	-4.34E-05		**0.074**	-0.010	-0.014	-0.012	-0.006	**-0.026**	**-0.023**
t-stat	1.03	**7.12**	0.76	0.37	0.38	**2.13**	0.66	-0.23		**5.00**	-0.86	-1.36	-1.04	-0.43	**-2.42**	**-2.83**

Panel C: TSE

	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6
r	-0.001		0.023	**0.027**	0.010	0.000	-0.010	-0.015	**2.089**	0.085	0.093	-0.006	-0.243	-0.122	0.159
t-stat	-0.84		1.80	**2.41**	1.05	-0.03	-1.09	-1.56	**9.94**	0.46	0.62	-0.04	-1.57	-0.69	0.83
x	0.000	**2.78E-03**	1.73E-04	1.59E-04	1.87E-04	**6.17E-04**	2.54E-05	1.25E-05		**0.063**	-0.014	-0.012	-0.011	-0.005	**-0.029**
t-stat	-0.62	**7.59**	0.72	0.71	0.76	**2.63**	0.10	0.06		**4.13**	-1.08	-1.11	-0.91	-0.36	**-2.40**

Panel D: TSE, Control TO

	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6	TO
r	**-0.005**		0.005	0.017	0.007	0.000	-0.012	-0.016	**2.025**	0.033	0.085	-0.022	-0.244	-0.081	0.151	**2.163**
t-stat	**-5.46**		0.42	1.61	0.75	0.00	-1.32	-1.73	**9.91**	0.18	0.60	-0.15	-1.60	-0.51	0.82	**6.41**
x	0.000	**2.85E-03**	1.37E-04	1.30E-04	1.97E-04	**6.00E-04**	1.01E-04	2.20E-05		**0.063**	-0.013	-0.013	-0.010	-0.006	**-0.029**	**-0.022**
t-stat	1.76	**8.43**	0.57	0.59	0.85	**2.51**	0.40	0.11		**4.17**	-1.04	-1.17	-0.85	-0.43	**-2.40**	**-2.74**

Table IV. Dealer Order Flow and Stock Return VAR, Lagged Independent Variables Only

This table reports weighted Fama-MacBeth (1973) style regression results for the following standard VAR specification, including only lagged independent variables:

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

r is weekly stock return (excess over the value-weighted index), *x* is weekly aggregate dealer net order flow (net trade / shares outstanding), and *TO* is overall market turnover. Only listed (TSE) stocks are used. 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 order flow regressions), and x0 – x6 refer to the regression coefficients on independent dealer order flow variables (B_0-B_6 for the return regressions and D_1-$D_6$for the order flow regressions). **Bold** indicates |t-statistic| ≥ 2. Boxed indicates a group of lagged variable coefficients with consistent signs, which may indicate significant relations.

Standard VAR (Lags Only): TSE, Control TO

	Intercept	r1	r2	r3	r4	r5	r6	x1	x2	x3	x4	x5	x6
r	-0.001	0.024	**0.026**	0.009	0.001	-0.010	-0.015	0.208	0.134	-0.003	-0.242	-0.076	0.136
t-stat	-0.722	1.870	**2.384**	0.970	0.057	-1.040	-1.582	1.130	0.879	-0.017	-1.583	-0.435	0.703
x	0.000	1.45E-04	1.29E-04	1.52E-04	**6.02E-04**	-5.37E-05	-2.03E-05	**0.063**	-0.013	-0.013	-0.012	-0.005	**-0.029**
t-stat	-0.379	0.620	0.577	0.634	**2.508**	-0.214	-0.098	**4.119**	-1.032	-1.171	-0.946	-0.384	**-2.349**

Table Va. Dealer Order Flow and Stock Return VAR, Stock Quartiles by Market Capitalization

This table reports pooled regression results for the following VAR specification across three types of quartiles:

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

r is weekly stock return (excess over the value-weighted index, except in *Panel A* where it is excess over the appropriate value-weighted quartile index return), *x* is weekly aggregate dealer net order flow (net trade / shares outstanding), and *TO* is overall market turnover. All specifications use only listed (TSE) stocks. Standard errors are estimated with a bootstrap procedure described in Section IIIA.

Panel A reports results for stock size quartiles (4=largest), sorting stocks by market capitalization at the beginning of each year. 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 order flow regressions), and x0 – x6 refer to the regression coefficients on independent dealer order flow variables (B_0-B_6 for the return regressions and D_1-$D_6$for the order flow regressions). **Bold** indicates |t-statistic| ≥ 2. Horizontal-Boxed indicates a group of lagged variable coefficients with consistent signs, which may indicate significant relations. Vertical-Boxed indicates a pattern across quartiles in the t-statistics that may indicate an economic relationship across quartiles.

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

	StockSize	Intercept	r0	r1	r2	r3	r4	r5	r6	x0	x1	x2	x3	x4	x5	x6	TO
r	1	**0.002**		**0.067**	-0.001	0.009	-0.010	0.009	-0.008	0.625	0.102	**-0.876**	0.326	-0.414	-0.026	0.135	0.083
t-stat		**2.04**		**3.22**	-0.06	0.50	-0.55	0.52	-0.53	1.34	0.29	**-2.75**	1.19	-1.22	-0.08	0.36	0.45
r	2	**-0.004**		0.034	0.005	-0.004	0.010	0.005	-0.005	0.592	0.031	0.025	**-0.362**	**-0.532**	0.343	0.174	**2.199**
t-stat		**-5.29**		1.84	0.35	-0.25	0.67	0.40	-0.36	1.90	0.18	0.13	**-2.03**	**-2.54**	1.92	1.07	**6.37**
r	3	**-0.005**		0.007	0.029	-0.011	-0.012	-0.022	-0.010	**1.477**	0.019	0.015	-0.012	-0.142	-0.110	-0.201	**3.081**
t-stat		**-6.26**		0.44	1.74	-0.68	-0.86	-1.53	-0.80	**7.18**	0.11	0.10	-0.06	-0.81	-0.56	-1.21	**9.36**
r	4	**-0.006**		-0.015	0.024	0.019	-0.013	-0.019	-0.027	**2.635**	-0.094	0.204	-0.106	0.016	-0.199	-0.132	**4.532**
t-stat		**-5.99**		-0.84	1.36	1.06	-0.78	-1.12	-1.81	**8.97**	-0.42	0.85	-0.51	0.07	-1.03	-0.58	**8.80**
x	1	**-0.126**	7.20E-04	7.87E-04	6.65E-04	2.01E-04	4.50E-04	**-6.44E-04**	2.26E-04		**0.293**	-0.021	0.054	0.019	-0.023	0.000	**-0.005**
t-stat		**-4.15**	1.29	1.31	1.56	0.56	1.41	**-2.26**	0.70		**4.76**	-0.47	1.76	0.69	-0.78	0.01	**-2.23**
x	2	-0.038	1.13E-03	-2.04E-04	3.73E-04	3.00E-04	-2.51E-04	-3.41E-05	1.16E-04		**0.092**	-0.006	-0.006	0.004	-0.011	-0.002	**-0.028**
t-stat		-1.50	1.88	-0.51	1.07	0.89	-0.66	-0.09	0.38		**2.01**	-0.22	-0.24	0.18	-0.67	-0.09	**-2.76**
x	3	-0.042	**2.56E-03**	2.23E-04	-2.53E-04	-5.24E-04	4.60E-04	3.01E-04	4.24E-04		-0.004	-0.027	-0.003	-0.022	0.005	**-0.039**	-0.014
t-stat		-1.85	**7.03**	0.68	-0.67	-1.78	1.50	1.05	1.31		-0.22	-1.58	-0.17	-1.11	0.35	**-2.08**	-1.18
x	4	**-0.042**	**2.51E-03**	1.86E-04	-8.33E-05	-1.20E-04	**4.73E-04**	-5.34E-05	-8.53E-05		-0.002	-0.017	-0.018	**-0.046**	0.009	-0.002	0.005
t-stat		**-2.27**	**8.50**	0.75	-0.39	-0.48	**2.10**	-0.22	-0.38		-0.14	-1.31	-1.26	**-2.74**	0.67	-0.14	0.58

Table Vb. Dealer Order Flow and Stock Return VAR, Stock Quartiles by Dealer Turnover

This table reports pooled regression results for the following VAR specification across three types of quartiles:

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

r is weekly stock return (excess over the value-weighted index), *x* is weekly aggregate dealer net order flow (net trade / shares outstanding), and *TO* is overall market turnover. All specifications use only listed (TSE) stocks. Standard errors are estimated with a bootstrap procedure described in Section IIIA.

Panel B reports results 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). 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 order flow regressions), and x0 – x6 refer to the regression coefficients on independent dealer order flow variables (B_0-B_6 for the return regressions and D_1-$D_6$for the order flow regressions). **Bold** indicates |t-statistic| ≥ 2. Horizontal-Boxed indicates a group of lagged variable coefficients with consistent signs, which may indicate significant relations. Vertical-Boxed indicates a pattern across quartiles in the t-statistics that may indicate an economic relationship across quartiles.

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

	GrossTO	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
t-stat		**-2.08**		**2.09**	0.74	0.72	-0.66	0.26	-1.46	0.96	-1.23	-0.97	**-2.30**	**-2.35**	-1.20	1.16	1.44
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**
t-stat		**-5.33**		0.33	1.77	1.77	-1.27	-1.09	-1.53	1.71	0.68	-1.60	-1.49	1.13	**-2.23**	-0.26	**5.33**
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**
t-stat		**-6.10**		0.37	1.58	1.05	-0.38	0.63	-0.68	**3.49**	**-2.59**	0.50	-1.92	-0.69	-0.28	-0.02	**8.46**
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		**-3.53**		-0.08	**2.21**	0.51	0.07	-0.14	-0.36	**9.01**	0.45	-0.23	-0.86	-1.19	0.58	-0.04	**8.70**
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
t-stat		**-2.57**	0.97	1.25	0.91	0.26	0.06	0.44	0.12		**4.08**	-0.16	1.63	-0.69	0.14	0.29	-1.74
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**
t-stat		**-4.06**	1.71	-1.21	-0.09	-0.98	-0.36	0.38	-0.61		**5.06**	1.93	1.59	-0.23	0.70	0.78	**-2.41**
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**
t-stat		**-2.45**	**3.21**	1.58	0.53	-0.12	0.63	0.74	1.52		**6.38**	**2.00**	**2.57**	0.96	0.40	-0.05	**-2.31**
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		-0.39	**8.57**	0.72	0.14	0.10	**2.17**	-0.20	0.66		1.92	-1.51	-0.77	-1.73	-0.20	-1.56	**-2.49**

Table Vc. Dealer Trade and Stock Return VAR, Dealer Quartiles by Dollar Volume Traded

This table reports pooled regression results for the following VAR specification across three types of quartiles:

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

r is weekly stock return (excess over the value-weighted index), *x* is weekly aggregate dealer net order flow (net trade / shares outstanding), and *TO* is overall market turnover. All specifications use only listed (TSE) stocks. Standard errors are estimated with a bootstrap procedure described in Section IIIA.

Panel C reports results for dealer quartiles (4=largest), sorting dealers by dollar volume in the previous year (except in 1997, the 1997 sorting is applied). 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 order flow regressions), and x0 – x6 refer to the regression coefficients on independent dealer order flow variables (B_0-B_6 for the return regressions and D_1-$D_6$for the order flow regressions). **Bold** indicates |t-statistic| ≥ 2. Horizontal-Boxed indicates a group of lagged variable coefficients with consistent signs, which may indicate significant relations. Vertical-Boxed indicates a pattern across quartiles in the t-statistics that may indicate an economic relationship across quartiles.

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

	Volume	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**
t-stat		**-3.09**		0.88	**2.88**	1.12	-0.40	0.29	-0.91	-0.97	-0.74	1.00	0.47	-1.39	0.80	-0.75	**3.51**
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**
t-stat		**-5.83**		-0.36	**2.02**	0.64	-0.17	-0.71	-1.20	-0.72	1.91	1.16	-0.16	0.28	0.66	1.52	**7.38**
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**
t-stat		**-4.02**		0.63	**2.37**	1.33	0.05	0.66	-1.04	**4.37**	-1.08	-0.65	-0.74	0.28	0.07	-1.14	**4.60**
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		**-5.70**		-0.03	**2.23**	0.84	0.19	0.43	-1.12	**8.93**	-1.36	-0.82	-1.73	-0.64	-0.88	0.25	**8.48**
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
t-stat		-0.86	-1.07	0.90	0.55	1.76	0.29	1.44	1.33		1.19	0.99	1.48	0.04	0.47	1.53	-1.73
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**
t-stat		0.44	-0.66	**-3.02**	0.48	**-2.01**	-0.40	0.03	0.43		0.02	-1.38	-1.04	0.42	-0.14	0.78	**-3.02**
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
t-stat		**-5.87**	**4.20**	-0.46	-0.52	-1.32	0.87	1.36	0.50		**4.43**	0.74	**2.56**	-0.55	-1.52	-0.85	-1.14
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	4	-1.10	**7.87**	1.98	-0.02	-1.30	1.90	-1.01	1.06		**2.48**	-0.91	-1.07	-1.35	0.53	**-2.21**	**-4.03**

Table VIa. Dealer Profit Decomposition, Dollar Decomposition

The table reports details about dealer profits. Dollar profits for each dealer in each stock in each week are decomposed into Information (Info), Market making (MM), and Mixed (Mix) components. Profits to each component are aggregated across dealers and stocks for each time period, and significance tests are done with time-series profits.

$$\prod = [InformationComponent] + [MarketMakingComponent] + [MixedComponent]$$
$$\prod (NetTrade+) = [INV_{t-1} * P_{t-1} * r_t] + [GrossSell * (P_{sell} - P_{buy})] + [NetBuy * (P_t - P_{buy})]$$
$$\prod (NetTrade-) = [INV_t * P_{t-1} * r_t] + [GrossBuy * (P_{sell} - P_{buy})] + [NetBuy * (P_{t-1} - P_{sell})]$$

"NetTrade+" ("NetTrade-") denotes a week in which the dealer was a net buyer (seller) of the stock. See Section II for a detailed description and justification of the profit decomposition. *Panel A* reports the raw dollar profits to each component in NT$1000s, in aggregate and across stock capitalization quartiles (4=largest). 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: Dollar Profit Decomposition (NT$1,000s)

	N	Total	Info	MM	Mix
Aggregate	239	$ 130,790	$ 122,142	$ (393)	$ 9,041
		0.81	0.90	-0.11	0.33
Quartile 1	239	$ (7,898)	**$ (9,007)**	$ 68	$ 1,041
		-1.85	**-2.28**	0.69	1.78
Quartile 2	239	$ (7,180)	$ (11,569)	**$ 765**	**$ 3,623**
		-0.57	-1.01	**3.96**	**2.70**
Quartile 3	239	$ (316)	$ (11,012)	**$ 2,692**	**$ 8,005**
		-0.01	-0.42	**5.34**	**2.30**
Quartile 4	239	$ 146,183	$ 153,729	$ (3,918)	$ (3,628)
		1.17	1.51	-1.23	-0.15

Table VIbc. Dealer Profit Decomposition, Return Decomposition and Risk-Adjusted Returns

Panel B reports the return to each component and quartile in *Panel A*, where the base for return calculations is the beginning-of-week inventory value of stocks held in aggregate or in the appropriate quartile. *Panel C* reports risk-adjusted returns to the market making profits and inventory profits. The base for inventory returns is the beginning-of-week value of inventory held for the entire week, and the base for market making returns is the average between buy and sell values of positions opened and closed in the same week. Inventory returns are further adjusted by the appropriate value-weighted index. Returns for *Panel B* are average weekly returns in percent (market making returns in *Panel C* are roughly half-weekly; the period cannot be determined exactly with our weekly data). **Bold** indicates statistical significance, i.e. |t-statistic| ≥ 2, and t-statistics are placed below returns.

Panel B: Return Profit Decomposition, Base (NT$1,000,000s)

	N		Base	Total	Info	MM	Mix
Aggregate	239	**$**	**51,456**	0.284%	0.257%	0.004%	0.024%
			40.97	0.94	1.01	0.52	0.47
Quartile 1	239	**$**	**1,486**	**-0.815%**	**-0.883%**	0.006%	0.063%
			28.40	**-2.67**	**-3.08**	1.30	1.84
Quartile 2	239	**$**	**4,109**	-0.124%	-0.232%	**0.020%**	**0.088%**
			48.25	-0.43	-0.87	**4.35**	**2.82**
Quartile 3	239	**$**	**9,439**	0.070%	-0.054%	**0.033%**	0.091%
			46.35	0.23	-0.20	**5.60**	2.30
Quartile 4	239	**$**	**36,422**	0.466%	0.461%	-0.004%	0.009%
			34.90	1.44	1.75	-0.39	0.14

Panel C: Risk-Adjusted Returns, Bases (NT$1,000,000s)

	N		BaseInfo	Info	Index	Info - Index		BaseMM	MM
Aggregate	239	**$**	**45,963**	0.347%	-0.072%	**0.418%**	**$**	**3,168**	-0.133%
			41.29	1.20	-0.25	**5.61**		**22.09**	-1.29
Quartile 1	239	**$**	**1,432**	-0.828%	**-0.922%**	0.094%	**$**	**45**	**0.425%**
			29.14	-2.90	**-3.36**	0.77		**8.29**	**2.25**
Quartile 2	239	**$**	**3,880**	-0.188%	-0.503%	**0.314%**	**$**	**101**	**0.801%**
			48.91	-0.67	-1.65	**3.37**		**14.08**	**5.05**
Quartile 3	239	**$**	**8,703**	0.037%	-0.346%	**0.382%**	**$**	**411**	**0.564%**
			46.09	0.12	-1.16	**5.29**		**16.97**	**4.97**
Quartile 4	239	**$**	**31,948**	0.587%	0.049%	**0.538%**	**$**	**2,611**	**-0.265%**
			35.13	1.91	0.17	**6.68**		**19.57**	**-2.24**

Table VII. 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 (*Stdev*) and kurtosis (*Kurt*) of daily returns as well as relative dealer trading volume (aggregate dealer trading volume / total market volume) for each stock. Regression specifications are shown in each panel. We implement Fama and MacBeth (1973) style regressions, i.e. cross-sectional regressions in each time period and weighted (by degrees of freedom) time-series parameter estimates and t-statistics. All coefficients are statistically significant, and the effects of volatility and kurtosis on dealer relative volume are independent.

Panel A: RelativeVolume = βStdev + ε

Weighted Measure	N	Intercept	β
Mean	66	0.056	-0.524
t-stat	66	11.23	-4.10

Panel B: RelativeVolume = βKurt + ε

Weighted Measure	N	Intercept	β
Mean	66	0.037	0.003
t-stat	66	27.60	4.46

Panel C: RelativeVolume = β1Stdev + β2Kurt + ε

Weighted Measure	N	Intercept	β1	β2
Mean	66	0.048	-0.302	0.002
t-stat	66	10.43	-2.48	2.99

Table VIII. 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)*. "MOD" 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). Both measures are statistically significant in aggregate and in size quartiles.

Contemporaneous Correlation of Dealer Trades

	N	MOD	MOD 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