Day Trading in Equilibrium

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IMPORTANT NOTE:

This paper is undergoing a substantial revision. The current draft of the paper is very much a work in progress. Comments welcome !

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Preliminary and incomplete. Do not quote.

Day Trading in Equilibrium

Abstract

We analyze the cross-sectional differences in the performance of individual investors who engage in day trading in Taiwan. Consistent with prior research on the performance of individual investors, we document that in aggregate day traders lose money. However, we find striking evidence that a select few individual investors (less than 1 percent of the day trading population) are able to consistently earn abnormal profits net of fees. Our results contribute to the evidence that cross-sectional variation in investor ability is an important feature of financial markets.

Preliminary and incomplete. Do not quote.

On average, individual investors lose money from trading. Barber and Odean (2000) document that the majority of losses incurred at one large discount broker in the U.S. can be traced to trading costs. However, trading costs are not the whole story. On average, individual investors have perverse security selection abilities; they buy stocks that earn subpar returns and sell stocks that earn strong returns (Odean (1999)). In aggregate, the losses of individuals are material. Barber, Lee, Liu, and Odean (BLLO, 2008), using complete transaction data for the Taiwan market from 1995 to 1999, document the aggregate losses of individual investors exceed two percent of annual Gross Domestic Product in Taiwan.

In this research, we extend this line of inquiry by focusing on day trading. As in BLLO (2008), we use complete transaction data for the Taiwan Stock Market, but use a much longer sample period of 1992 to 2006. We focus on day trading for two reasons. First, we are interested in analyzing the cross-section of individual investor performance. With a long time-series of data for thousands of day traders, we are able to focus on a population of individual investors who are receiving quick clear feedback about their trading ability. It is among this group that we are most likely to identify persistently good traders. Second, day trading by individual investors in financial markets is not well understood. As such, our paper provides an important description of day trading by individual investors, which appears to be an important equilibrium feature of many emerging markets – most notably mainland China.

We define day trading as the purchase and sale of the same stock by the same investor on the same day. We analyze the performance of day traders in two parts: (1) the intraday returns earned on trades (i.e., the day trading return), and (2) the return on the remaining portfolio (or open positions). The day trading return includes both round-trip and one-sided trades, while the remaining portfolio return includes the returns to all positions that remain open after the day of trade. Thus, we completely and accurately account for all gains and losses earned by day traders.

In aggregate, consistent with prior work on individual investors, day traders lose money. The gross losses to day trading are reliably negative in 13 of the 15 years that we analyze. (In aggregate, the returns on the remaining portfolio are not reliably different from zero.) From an industrial organization perspective, day trading is an industry that consistently loses money. We discuss why this might be an equilibrium outcome after presenting results.

Most importantly, we document predictable cross-sectional variation in the profitability of day trading. In the average year, about 360,000 Taiwanese individuals engage in day trading. In a simple univariate sort on past profit, we document that only the top 4,000 day traders (about one percent of the total population of day traders) from the prior year are able to earn reliably positive profits net of trading costs in the subsequent year. To our knowledge, this is the first large-scale study that documents some individual investors earn trading profits net of transaction costs.

In auxiliary analyses, we document that several factors predict future profitability including past profitability, past day trading volume, the willingness to short, and the concentration of trading in a few stocks. While several studies document variation in performance using data from a large U.S. discount brokerage firm, there are no studies that we are aware of that document individual investors are able to cover trading costs with superior security selection.[1] We find that the ability to cover costs, though rare, is possible for a select few.

Just as striking are the variables that do not predict profitability. We do not find that experience (measured by the number of days of day trading) improves performance. We also find little evidence that day traders are profiting by serving as liquidity providers. If anything, day traders appear to place more aggressive orders than other

[1] The following papers use trading records at a large U.S. brokerage firm and document variation in performance: Coval, Hirshleifer, and Shumway (2005) (related to past performance), Ivkovich and Weisbenner (2005) (geography), Ivkovich, Sialm, and Weisbenner (2007) (portfolio concentration), Korniotis and Kumar (2008) (cognitive abilities).

traders. Furthermore, the aggressiveness of orders underlying trades is, at best, a weak predictor of future profitability.

The rest of this paper is organized as follows. In section I, we present related research and regulatory issues. We discuss Taiwan market rules, our dataset, and methods in Section II. We present results in Section III, followed by a discussion and concluding remarks.

I. Background and Related Research

Day trading has been the subject of numerous regulatory hearings in the U.S. In 1999, The Electronic Trade Association estimated that 4,000 to 5,000 people traded full time through day trading brokerages[2] and accounted for nearly 15 percent of daily volume on NASDAQ.[3] By most accounts, the poor returns on U.S. stocks from 2000 to 2002 squelched day trading. However, as the U.S. market earned strong returns in 2003, day trading made a comeback.[4]

In September 1999, the Senate Permanent Subcommittee on Investigations held the first congressional hearing on day trading. In July 2000, the subcommittee issued its final report. The report concluded that (p.2) "a growing number of people are giving up their existing careers or withdrawing their savings to become full-time professional day traders." Concurrent investigations were launched by the SEC, NASD, NYSE, and several state regulatory bodies. All of these investigations expressed concerns about the potentially deceptive advertising practices employed by day trading firms. As a result of these investigations, the NYSE and NASD adopted rules in September 2001 that required day trading firms to make a determination that day trading is appropriate for a particular customer.

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[2] Randy Whitestone and Phil Serafino, *Day Traders' Invasion,* BLOOMBERG, May 1999, at 36, 39.
[3] Britt Tunick, *Day Traders Working Hard to Influence How the Profession is to be Defined*, SEC. WEEK, May 24, 1999.
[4] John Hechinger and Jeff Opdyke, *Day Trading Makes a Comeback and Brokers Vie for the Business*, Wall Street Journal, September 30,2003, p.A1. Matt Krantz, *Day Traders Make a Comeback*, USA Today, July 28, 2003.

Do day traders make money? This was a central question in the investigations described above. Unfortunately, to date, there is no comprehensive empirical evidence available to answer this question. Though the investigations contained some analyses of the profitability of day trading, these analyses were largely limited to a handful of accounts. For example, the North American Securities Administrators Association sponsored a widely cited study of the profitability of 26 day traders at All-Tech brokerage, a brokerage that catered to day traders and was a target of the Senate investigations. Clearly, a small sample of accounts from a brokerage firm under investigation is not representative of the day trading population.

Unlike the studies cited in congressional and SEC investigations, three small scale academic studies of day trading provide evidence that day trading can be profitable. Harris and Schultz (1998) analyze the day trading of Small Order Execution System (SOES) bandits using trading records from two brokers. To do so, they analyze roughly 20,000 trades over a three week period. Though the SOES traders lose money almost as frequently as they make money, they earn a small average profit per trade. Similarly, Garvey and Murphy (2001) analyze the trading of 96,000 trades made by fifteen proprietary day traders—traders who use a firm's capital, pay no commissions, and profit share with the firm—at a direct access broker during three months in 2000. They too find these fifteen day traders are able to make money on their day trading activities primarily by placing limit orders on electronic crossing networks (ECNs) that are inside the current best quotes offered by NASDAQ dealers. Seasholes and Wu (2004) examine the trades of ten extremely active traders on the Shanghai Stock Exchange. These traders earn substantial profits through buying shares on days that stocks hit their upper price limits and quickly selling those shares the following day.

Linnainmaa (2003) analyzes 7,686 investors who complete at least one roundtrip intraday transaction. These investors are far less active than those studied by Harris and Schultz (1998) and Garvey and Murphy (2001). The majority of these investors day trade on only one or two occasions and, in aggregate, these investors complete only 185,000 day trading related trades over a two and a half year period (November 1998 through

May 2000). Linnainmaa reports that the net returns of these investors are lower than those of a control sample.

In contrast to these smaller scale studies of day trading, we provide a comprehensive analysis of the profitability of all day trading in Taiwan over a five year period. To do so, we use a unique and remarkably complete dataset, which contains the entire transaction data, underlying order data, and the identity of each trader on the Taiwan Stock Exchange (TSE). With these data, we provide a comprehensive accounting of the profitability of day traders during the period 1992 through 2006.

Taiwan provides a particularly appropriate setting to analyze the profitability of day trading. By most accounts, day trading has been a fixture on the TSE for decades. Consistent with these assertions, day trading accounts for almost 20 percent of trading volume in Taiwan during our 1992 to 2006 sample period (see Figures 1 and 2). Virtually all day trading (97.5 percent) can be traced to individual investors in Taiwan. In the typical month, 15 percent of individual investors who trade on the TSE engage in at least one day trade.

II. The Taiwan Market, Data, and Methods

II.A. Taiwan Market Rules

Before proceeding, it is useful to describe the Taiwan Stock Exchange (TSE). The TSE operates in a consolidated limit order book environment where only limit orders are accepted. During the regular trading session, from 9:00 a.m. to noon during most of our sample period, buy and sell orders can interact to determine the executed price subject to applicable automatching rules.[5] Minimum tick sizes are set by the TSE and vary depending on the price of the security. Generally, orders are cleared using automatching rules one to two times every 90 seconds throughout the trading day. Orders are executed in strict price and time priority. An order entered into the system at an earlier time must

[5] Trading also occurred on Saturdays during most of our sample period. Before December 1997, Saturday trading occurred from 9:00-11:00. From January to March, 1998, stocks were traded only on the second and the fourth Saturday in each month. From April 1998 to Decebmber 2000, Saturday trading occurred from 9 am to noon. From 2001 on, there has been no trading on Saturday.

be executed in full before an order at the same price entered at a later time is executed. Although market orders are not permitted, traders can submit aggressive price-limit order to obtain matching priority. During our study period, there is a daily price limit of seven percent in each direction and a trade-by-trade intraday price limit of two ticks from the previous trade price.

Since our analysis focuses on day trading, an important consideration is transaction costs. The TSE caps commissions at 0.1425 percent of the value of a trade. Some brokers offer lower commissions for larger traders – an issue that we discuss in greater detail later in the paper. Officials at brokerage firms and the TSE indicated to us that the largest commission discount offered is 50 percent (i.e., a commission of roughly 7 basis points); these same officials estimated the trade-weighted commission paid by market participants to be about 10 basis points. Taiwan also imposes a transaction tax on stock sales of 0.3 percent.

II.B. Trades Data and Descriptive Statistics

We have acquired the complete transaction history of all traders on the TSE from 1992 to 2006. The trade data include the date and time of the transaction, a stock identifier, order type (buy or sell -- cash or margin), transaction price, number of shares, a broker code, and the identity of the trader. The trader code allows us to broadly categorize traders as individuals, corporations, dealers, foreign investors, and mutual funds. The majority of investors (by value and number) are individual investors. Corporations include Taiwan corporations and government-owned firms (e.g., in December 2000 the government-owned Post, Banking, and Insurance Services held over $NT 213 billion in Taiwanese stock). Dealers include Taiwanese financial institutions such as Fubon Securities, Pacific Securities, and Grand Cathay Securities. Foreign investors are primarily foreign banks, insurance companies, securities firms, and mutual funds. During our sample period, the largest foreign investors are Fidelity Investments, Scudder Kemper, and Schroder Investment Management. Mutual funds are domestic mutual funds, the largest being ABN-AMRO Asset Management with $NT 82 billion invested in Taiwanese stocks in December 2000.

We define day trading as the purchase and sale, in any order, of the same stock on the same day by an investor. Specifically, if an investor buys and sells the same stock on the same day, we calculate the number of shares bought (S_b), the number of shares sold (S_s), the average purchase price (P_b), and the average sales price (P_s). The value of day trading is defined as half of the total value of sales and purchases ($½*P_b*\min(S_b,S_s)+ ½*P_s*\min(S_b,S_s)$). Over our sample period, day trading accounted for more than 17 percent of the total dollar value of trading volume. Most day trading (about 2/3^{rds}) involves the purchase and sale of the same number of shares in a stock over the course of one day (i.e., most day trades yield no net change in ownership at the close of the day).

In Figure 1, we plot day trading (black) and other trading (grey). There is clear variation in the volume of day trading and other trading over time, though the two are correlated (91% correlation at the monthly level). Though not the focus of our investigation, it is natural to wonder whether wide fluctuations in day trading (and total volume) can be explained by past market performance. Perhaps surprisingly, this does not appear to be the case; we regress of changes in day trading on past returns (alternatively at monthly, quarterly, or annual horizons) and find past returns has no ability to predict changes in day trading. In figure 2, we plot day trading as a percentage of total trading volume. While day trading was somewhat less prevalent in the early part of our sample period (perhaps because of restrictions on short selling, which were lifted at the end of 1993), the share of volume traced to day trading has been consistently around 20 percent of total trading volume from 1994 to 2006. Day trading is an equilibrium feature of the Taiwan stock exchange.

Virtually all day trading can be traced to individual investors. In the average month, individual investors account for 95 percent of day trading. Individuals and corporations are free to short sell, though dealers, mutual funds, and foreigners are prohibited from doing so on the TSE. These short sale restrictions might partially explain the tendency for day trading to concentrate among individual investors and corporations. In contrast to U.S. markets, dealers are not active providers of liquidity. Though dealers are required to "efficiently adjust the demand and supply in the market depending on the market situation, and ensure that the formation of fair price and its sound operation are not harmed," dealers face no specific penalties for failing to meet this requirement. Dealer trades emanate from their proprietary trading activity. Based on our discussions with dealers in the TSE, the majority of this proprietary trading is not necessarily intended to provide liquidity. Chae and Wang (2003) also report that TSE dealers are not net providers of liquidity. In the remainder of the paper, we focus on these individual investors.

In figure 3, we plot the number of individuals who day trade by month. In the average month, almost 140,000 individuals day trade. With an adult population of about 16 million (total population about 22 million), this means just shy of 1 percent of the adult population day trades in the average month. Though prevalent, day trading is heavily concentrated. In each year, we rank individuals based on the total value of their day trading activity. In figure 4, we plot the share of day trading that can be traced to the top 2,000 day traders (by volume), separately identifying the top 500, 501-1000, and 1001-2000. In the early 1990s, about half of all day trading could be traced to these active day traders, though since 1994 the share of day trading accounted for by these active traders is about 30 percent. Day trading is clearly an industry dominated by a few individuals, while tens of thousands individuals engage in relatively low levels of day trading.

II.C. Performance Measurement

Our performance measurement focuses on the intraday profits of all trades made by day traders. We separately analyze the long-run (interday) profitability of positions generated by these trades to ensure the inferences we draw from the analysis of intraday profits are accurate.

Consider the intraday returns to day trading. First, we identify all trades made by day traders. We calculate the profits on round-trip day trades and other trades which open positions. The other trades are either purchases to open a long position or sales that open a short position. The profits for trades that lead to an open position are calculated relative to closing prices on the date of the trade. To calculate the total return earned by day traders, we merely sum the proceeds from stocks sold for long positions and bought for short positions (or their mark-to-market equivalent at the close of the trading day) and divide by the cost of the stocks bought or sold short (or their mark-to-market equivalent at the close of trading on the prior day).

To calculate returns net of transaction costs, we assume a 10 bps round-trip commission and a 30 bps transaction tax on sales. Our assumption regarding commission costs (10 bps) is somewhat generous, but we do not want to erroneously conclude day traders lose money by assigning a transaction cost that might be higher than that actually paid.

Finally, we calculate the long-run (interday) returns to open positions. Positions for each investor are built from their prior trades.[6] This return on the remaining portfolio includes the returns earned on trades that close positions and the transaction costs associated with those trades. We can calculate the total profits earned by day traders by summing their day trading and long-run profits.

In figure 5, we present an example of four trades by a day trader. The red lines represent short positions, while the black lines represent long positions. The solid lines are the portion of returns that are included in our day trading profits, while the dashed lines are included in the analysis of long-run returns. It's clear from this graph that, by combining the two analyses, we capture the full experience of a trader.

To evaluate the performance of day traders, we estimate abnormal returns by regressing the portfolio excess return (portfolio return less riskfree rate) on the excess return on a value-weighted market index. We construct our own market index using market capitalization from the Taiwan Economic Journal (TEJ) and individual stock returns calculated from the TSE data. The intercept of this regression is our measure of abnormal returns.

[6] There are inevitably some errors in building positions since we do not know positions at the beginning of the dataset (in January 1992). While short sales are identified by their order type, buys to cover short positions are not. Thus, we may erroneously build a long position for purchases early on in the dataset.

III. Results

III.A. Preliminaries – Aggregate Performance

In table 1, we present the gross and net performance of all day traders. Though our performance analysis weights investors by the investments they make, we do not distinguish occasional day traders from active day traders in this preliminary analysis. We analyze the day trades and other trades of these investors in the months in which they day trade.

There are two reasons that including all trades in the month of day trading might positively bias our performance analysis. First, day traders are more likely to close profitable positions (consistent with the well-documented disposition effect).[7] Thus, months in which we observe day trading are more likely to be profitable months. Second, it is possible that good investment performance leads to day trading (i.e., reverse causation). We suspect both biases are small – particularly for active day traders who represent that vast majority of day trading. Regardless of the magnitude of the bias, we are not concerned by its presence in this preliminary analysis since we document poor performance in aggregate.

In the second column, we present the gross performance of day traders. On average, day traders lose 10 basis points on their day trading before costs (t=-12.40). Trading costs more than double the losses to 25 basis points per day. Moreover, we observe reliably negative gross and net performance in all years buy 1992. The return on the remaining portfolio (i.e., open positions) and the total portfolio return are presented in the last eight columns of table 1. The remaining portfolio also earns a negative alpha, so the total losses of day traders are negative.

In aggregate, day trading is a losing proposition. In other words, day trading is an industry that consistently and reliably loses money. From an industrial organization perspective, it is difficult to understand how such an industry survives. For people to knowingly day trade, they must either be overconfident about their prospects of success

[7] Footnote with references to the disposition effect.

or enjoy the activity and knowingly suffer losses as a result. Finally, the poor aggregate performance of day trading is not consistent with the learning model of Mahani and Bernhardt (2007). In their model, novice speculators lose while the experienced profit, but aggregate performance should be positive and represent the equilibrium return to day trading. We discuss this issue in detail after presenting our results.

III.B. Active Day Traders

In table 2, we present the gross and net performance of day traders based on prior day trading activity. In each year from 1992 to 2005, we rank day traders based on the dollar volume of day trading. We create nine groups based on prior activity – starting with the top 500 day traders and going on down to those with no prior day trading experience. We analyze the performance of each group in the year subsequent to ranking, thus eliminating the two sources of positive performance bias that we discussed before (disposition effect and reverse causation).

Consider the top 500 day traders (first row of table 2). These investors account for 10% of all day trading and 43% of their trades are round-trip day trades. They earn positive gross returns on their day trading of 13 basis points per day, but these profits do not survive costs and active day traders lose about 7 basis points per day net of fees. The active traders also earn positive (albeit unreliably so) alphas of 1 bps per day on the remainder of their portfolio. However, the total portfolio earns a reliably negative alpha (2.2 bps per day, t=-3.11).

It is clear from table 2 that active day traders, despite failing to make money net of costs, suffer less than occasional day traders. The performance of day trading, the remaining portfolio, and the total portfolio is nearly monotonically decreasing as one moves from the most active day traders (top row of table 2) to the least active day traders (bottom row of table 2).

In their analysis of the performance of individual and institutional investors in Taiwan from 1995 to 1999, Barber, Lee, Liu, and Odean (2008) document that, in aggregate, the trades of all individual investors lose money *before* transaction costs and that these losses grow at longer horizons. Thus the trades of both less active day traders and individual investors in aggregate lose money, while the trades of heavy day traders earn gross profits.

In summary, active traders perform better than occasional day traders, but are still unable to cover trading costs. Nonetheless, the security selection ability of active day traders, which generates gross daily alphas of 13 basis points, is impressive. The fact that performance improves with trading intensity is consistent with the learning model of Mahani and Bernhardt (2007); the fact the active day traders lose money is not.

III.C. Performance Persistence

In table 3, we present the performance of day traders sorted on the basis of prior profitability. We rank past profitability based solely on day trading returns. To measure profitability, we use the Sharpe ratio of past daily returns. We require a minimum of 10 days of day trading to rank an investor. Most of the gains (and losses) from trade tend to occur immediately following a trade (see Barber, Lee, Liu, and Odean (2008), Coval, Shumway, and Hirshleiffer (2005)). So, by focusing on day trading returns we are likely to obtain a more precise measure of trading ability. The returns on the remaining portfolio will contain many old positions that are no longer generating abnormal returns thus creating noise that might mask our ability to measure skill.

We create nine groups based on prior day trading profitability – starting with the top 500 day traders and going on down to those with no prior day trading experience. The top 500 traders have a mean Sharpe ratio of 0.21. Each of the top six groups (through 8,000 traders) has a mean Sharpe ratio greater than zero in the ranking period. We analyze the performance of each group in the year subsequent to ranking.

There is clear performance persistence. The top-ranked profit group (1 to 500) earns impressive alphas on their day trading, open positions, and their total portfolio. The top three groups (or 2,000 traders) earn reliably positive alphas on their day trading portfolio *net* of fees. In contrast, poor performers from prior years or those with insufficient history to be ranked earn reliably negative returns on their day trading and total portfolio.

In the average year, 360,000 individual engage in day trading. While about 13 percent earn profits net of fees in the typical year, the results of our analysis suggest that only about 1 percent of day traders (2,000 out of 360,000) are able to *consistently* outperform.

It is worth emphasizing the outsized alphas earned by the top day traders. They pick up 49 basis points on their day trading portfolio before costs and 28 basis points after costs *per day*. Their total portfolio earns a daily alpha of 1.8 basis points *per day*. Given a trading day of 280 days (with Saturday trading), this translates into an annual alpha of over 5 percentage points annually. In contrast, day traders ranked below the top 10,000 are giving up 5.7 basis points per day or over 15 percentage points annually.

III.D. Results by Order Type

Many day traders consistently earn gross profits, though only a select few are sufficiently savvy to consistently earn profits net of transaction costs. To gain further insight into the behavior of day traders, we analyze the orders underlying their trades. On one hand, day traders may provide liquidity to market participants by placing passive limit orders that provide depth to an otherwise thin market. This strategy would be profitable as long as uninformed traders are willing to pay for this liquidity and the providers of liquidity are able to avoid excessive trading with investors who possess superior information. On the other hand, day traders could earn gross profits by placing aggressive orders in anticipation of future price movements. This strategy would be profitable if day traders possessed superior information (or superior ability to process publicly available information) or were able to otherwise identify short-term trends in prices.

To determine whether day traders are earning gross profits by providing liquidity or spotting short-term trends in prices, we analyze orders underlying their trades. In addition to trade data, we have all orders (both filled and unfilled) that underlie these trades. Using these order data, we categorize each trade as aggressive or passive based on the order underlying the trade. This categorization involves three steps. First, for each stock, we construct a time series of clearing prices, the lowest unfilled sell limit order price, and the highest unfilled buy limit order price. These data are compiled by the TSE (the market display data) and are presented to market participants in real time. Second, we categorize all orders as aggressive or passive by comparing order prices to the most recent unfilled limit order prices. Orders to buy with prices in at, or in excess, of the most recent unfilled sell limit order are categorized as aggressive; those with prices at, or below, the most recent unfilled buy limit order are categorized as passive; those with an order price between the two unfilled limit order prices are categorized as indeterminate. There is an analogous algorithm for sells. Third, we match all orders to trades. This matching allows us to determine whether a trade emanated from a passive or aggressive order. Using this algorithm, we are able to categorize over 90 percent of all trades as passive or aggressive.[8]

Overall, about 2/3rds individual investors' trades can be traced to aggressive limit orders. (These proportions are calculated as the total number of aggressive trades divided by the sum of passive and aggressive trades.) The proportion is similar for institutional investors, though corporations tend to be more passive than foreigners and dealers. Even if investors placed similar numbers of aggressive and passive limit orders, we would expect a higher percent of trades to originate from aggressive limit orders, since aggressive limit orders are more likely to execute.

In Figure 6, we plot the proportion of trades that emanate from aggressive limit order for groups formed on the basis of day trading volume. We base our rank on total dollar volume of day trading in year t and analyze the aggressiveness of trades in year $t+1$. It is clear from the figure that heavy day traders tend to place aggressive limit orders. Among the top 5,000 day traders, 77 percent of trades can be traced to aggressive limit order, while the proportion drops to 69 percent for those who day trade little in the prior

[8] The indeterminate category also includes trades that we are unable to match to an order. We discussed this issue with the TSE and they suspect data entry errors in the order records is the source of the problem. Though annoying, this type of data error should not introduce any bias into our results.

year (rank > 50,000) and drops further to 63 percent for those who did not day trade in the prior year. These results suggest the gross returns earned by day traders do not appear to be compensation for the provision of liquidity.

We further explore this issue by ranking day traders an the aggressiveness of their orders in year *t* and analyzing their performance in year *t+1*. We create ten "aggressiveness" deciles ranging from one (most passive) to ten (most aggressive) based on the proportion of an investor's trades that emanate from aggressive limit orders. We further partition the top and bottom deciles in half to analyze the extremes more closely. We require that an investor make 100 trades which we classify as passive or aggressive to be included in the rankings. The most passive group (1a) has only 20 percent aggressive trades in the ranking year (and 28 percent in the following year), while the most aggressive group (10a) has 99 percent aggressive trades in the ranking year (and 97 percent in the following year).

In Table 4, we present the profitability of day trading based on the aggressiveness partitions. Focus first on the returns to day trading (columns two through seven of Table 4). All partitions lose money both before and after costs. The losses tend to be higher for the most aggressive partitions. The pattern of alphas for the remaining portfolio are consistent with those for the day trading return. It is also interesting to note that the passive day traders engage in less day trading (12 percent of trades are day trades) than their aggressive brethren (29 percent of trades are day trades).

III.E. Forecasting Profitability

Our analysis indicates several crude univariate sorts are able to forecast differences in the profitability of day traders. In this section, we employ a richer model to forecast the probability that a particular investor will be profitable. Our goal is twofold. First, we would like to better understand the variables that predict the profitability of day trading. Second, we would like to assess the spread in performance between the best and worst day traders.

We begin by estimating a logistic regression, where the dependent variable is a dummy variable that takes on a value of one if the net profits of a day trader in year *t* are positive. To reduce the impact of occasional entertainment day trading, we require that an investor engage in a minimum of $NT 600,000 in day trading. (We explore the use of higher and lower cutoff values and find generally similar results to those reported here.) Among this group, 13 percent of day traders earn profits net of cost in the average year. Of course, some day traders will earn net profits by mere chance, but our prior analysis of univariate sorts – particularly those based on past profits – indicates we are able to forecast future profitability as well.

We include a range of dependent variables designed to capture the experience, sophistication, and the skill of day traders. All independent variables are measured cumulatively through year *t-1*, while the dummy variable for profits is based on profitability in year *t*. We include two measures of past profits: **Sharpe Profit** and **Sharpe Return**. These Sharpe ratios are calculated as the mean net daily return (or profit) from day trading divided by the daily standard deviation. We include dollar profits to capture investors who might consistently earn low returns on a large capital base.

We include the concentration of an investor's trades in the five most traded stocks (**Percent Top Stock**). This variable is designed to capture any gains from specializing in the trading of a small group of stocks.

Short selling is a reasonable proxy for investor sophistication. Thus, we include the proportion of a day traders round-trip day trades that were short sales including buys to cover a short position (**Percent Short**). To capture whether there are gains to specializing in day trading, we measure the fraction of an investors trades that are round-trip day trades (**Fraction Day Trades**). The proportion of trades that are aggressive order measures whether a day trader is a liquidity demander or provider (**Fraction Agg. Trades**).

We include dummy variables for the number of days through year *t-1* the investor engaged in day trading. The default bin for the logistic regression is less than five days of prior experience, where we include additional ranges for 5-20, 21-70, 71-300, and greater than 300 days.

Finally, we include dummy variables for the dollar volume of day trading through year *t-1*. The default bin for the regression is less than $NT 900,000, were we include additional ranges for $NT 900,000 to 9 million, 9 to 45 million, 45 to 270 million, and more than 270 million.[9] For day traders with no prior experience, all variables are set to zero with the exception of the proportion of aggressive trades, which is set to the population mean of 70 percent.

We estimate logistic regressions for each year from 1994 to 2006. We begin in 1994 so as to allow some build-up in the history for the more experienced day traders. In table 5, we present the annual coefficient estimates, the mean coefficient estimate across year, and the standard error of the mean. In the first two rows of the table, we present the mean for each variable in the regression and the probability impact of each variable. The mean values are calculated weighting each year equally (i.e., calculate a mean for each year and then average across years).

The probability impact is measured as the change in probability from a baseline model. The baseline model sets all dummy variables to zero and all continuous variables to their mean values. For continuous variables, the probability impact is based on moving from the 25th to 75th percentile of the distribution of the independent variable under consideration while all remaining variables are set to zero (for dummy variables) or their mean (for continuous variables). For dummy variables, the probability change is based on moving from zero to one.

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[9] It is reasonable to ask whether multicollinearity may render coefficient estimates in these logistic regressions unstable. Multicollinearity does not seem to be a problem. The greatest pairwise correlation between any two variables is 51% between the dummy variables for more than 300 days of past day trading and total past day trading volume in excess of $NT 270 million. There are many frequent day traders who trade small sums and many high-volume day traders who infrequently engage in day trading.

As we discuss these results, it's useful to recall the baseline probabilities of earning a profit on one's day trading return is about 13 percent (i.e., 87 percent of day traders lose money unconditionally). Consistent with our univariate results, profitability measures are strong predictors of trading success. Both Sharpe ratios on returns and profits predict future success. Moving from the 25th to the 75th percentile on this variable improves the chances of being profitable by 6.1 percentage points for profits and 3.1 percentage points for returns. Similarly, heavy day traders have a much higher change of future earning future profits. The heaviest day traders (past volume greater than $NT 270 million) improve their chances of turning a profit by 10.9 percentage points relative to those who traded less than $NT 900,000 in the past.

It does not appear performance improves with experience. In fact, performance tends to decline with the number of prior days of day trading. This result also holds when we omit the volume of past day trading from these regressions. This results suggests that, in general, day traders do not learn by doing. If anything, the results suggest that the persistent day traders cling doggedly their erroneous beliefs regarding profitability or are simply addicted to the thrill of day trading.

We do find evidence that there are gains to specialization. Day traders who focus on a relatively few stocks tend to earn greater profits. Those who are willing to short sell also earn greater profits. Though statistically significant, these effects are economically modest and moving from the 25th to the 75th percentile on each variable only improves the probability of turning a profit by half or a percentage point.

In ongoing analyses, we are analyzing whether this performance model can be used to forecast future profits even more dramatically than simple sorts on past performance. Stay tuned for these results !

IV. Discussion

Most day traders, even heavy day traders, lose money trading. There are three noncompeting hypotheses that might explain why day traders persist in the face of losses: entertainment, preferences for skewed payoffs, overconfidence, and rational learning.

Undoubtedly some investors do find day trading entertaining. Can entertainment alone account for the extent of day trading that we observe? Do day traders knowingly and willingly accept such large expected losses for fun? For all but the wealthiest investors, this would be a very expensive form of entertainment indeed.

Another reason why day trading might entice investors would be if it provided an appealing distribution of returns. People often display an attraction to highly skewed investments, such as lotteries, that have negative expected returns but a small probability of a large payoff. However, the day trading profits that we document are similar in magnitude to, and far less prevalent than, losses. Unlike lottery winners, day traders must succeed on repeated gambles in order to achieve overall success. Such repeated gambles do not tend to generate highly skewed distributions.

Mahani and Bernhardt (2007) argue that some investors may willingly incur losses to learn about their trading ability. Several aspects of day trading in Taiwan are consistent with rational learning by market participants. There is tremendous cross-sectional variation in performance; heavy day traders perform better than light day traders; and, poor traders are more likely to quit. However, in aggregate, day traders should make money if rational learning was the only explanation for the presence of the large population of day traders.

A final potential explanation for the prevalence of day trading is that most day traders are overconfident about their own chances of success. Several papers (e.g., Odean (1998, 1999), Barber and Odean (2000, 2001)) argue that overconfidence causes investors to trade more than is in their own best interest. Overconfident day traders may simply be bearing losses that they did not anticipate. While day traders undoubtedly realize that other day traders lose money, stories of successful day traders may circulate in non-representative proportions, thus giving the impression that success is more frequent than it is. Heavy day traders, who earn gross profits but net losses, may not fully consider trading costs when assessing their own ability. And, individual day traders may believe themselves more likely to succeed than the average day trader. We are unable to explicitly test whether day traders are motivated by overconfidence rather than the desire for entertainment. Our opinion is that the average losses incurred by day traders are more than most would willingly accept as the cost of entertainment and that, by and large, day traders must hold unrealistic beliefs about their chances of success.

We find that the trades of heavy day traders are profitable before deducting transactions costs and that the trades of previously successful traders are profitable even after accounting for costs. How do day traders identify profitable trades and who is on the other side of these trades? The likely counterparties to profitable trades by heavy and previously successful day traders are less active day traders and individual investors in general. As documented in Section II.A and in Barber, Lee, Liu, and Odean (2008) the trades of both of these groups earn losses even before deducting transaction costs. One way in which day traders could be earning profits is by supplying liquidity through passive limit orders to uninformed investors who are too eager to pay for quick execution. While some day traders may focus on supplying liquidity, over 70 percent of the trades executed by heavy and previously successful day traders are aggressive limit orders; a similar proportion of their profits can also be traced to aggressive orders. Such orders will lead to day trading profits when traders are able to anticipate short term price changes. Harris and Shultz (1998) document that SOES bandits are able to profit from trading with market-makers who are ostensibly better informed and better financed. Harris and Shultz write that SOES bandits appear to profit by paying close attention to the market and reacting more quickly than most market-makers to changing market conditions. The day traders studied by Garvey and Ryan (2001) also appear to profit from reacting to market changes more quickly than most market makers. We speculate that the successful day traders who we observe profit by reacting more quickly than other investors to changing market conditions just as SOES bandits and the fifteen day traders studied by Garvey and Murphy profit from vigilance and quick reactions.

V. Conclusion

We analyze day traders in Taiwan. Day trading is prevalent in Taiwan – accounting for almost 20 percent of total trading volume during our sample period. Individual investors account for virtually all day trading (over 97 percent). Day trading is heavily concentrated. About 2,000 individual investors account for one third of day trading (or nearly 6 percent of total trading volume).

Our analysis of performance indicates day trading is treacherous, but not entirely a fool's game. Heavy day traders, as a group, earn gross profits (before transaction costs). Thus, heavy day traders do appear to have a trading advantage over other investors. Heavy day traders earn a gross return of 13 basis points *per day* on their day trading. Unfortunately, the gross profits of heavy day traders are not sufficiently large to cover reasonable estimates of transaction costs. Thus, as a group, they lose money. In contrast, occasional day traders experience both gross and net losses.

These results paint a rather dim portrait of day traders. However, we do document a select few (less than 1 percent of all day traders) are able to consistently earn profits sufficient to cover transaction costs. We identify day traders who earn substantial profits over a year and analyze the performance of their trades in the subsequent year. These profitable day traders continue to earn stellar returns. As a group, the top 500 day traders are able to earn a gross alpha of 49 basis points and a net alpha of 33 basis points *per day*. They also enjoy strong returns on their open positions.

Our analysis reveals the importance of varying ability in financial markets. While prior research has documented the average institution tends to earn strong returns at the expense of the average individual, our work indicates there is likely more cross-sectional variation within each group than between the average institution and average individual. This suggests that prior estimates of the losses incurred by individual investors are not shared by among all individuals, but are likely concentrated among those who either really enjoy trading or are ill-equipped to trade profitability in financial markets but nonetheless insist on doing so.

References

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2008, Just How Much Do Individual Investors Lose by Trading?, *Review of Financial Studies*, forthcoming.

Barber, Brad M., and Terrance Odean, 2000, Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors, *Journal of Finance*, 2000, Vol. 55, No. 2, p.773-806.

Barber, Brad M., and Terrance Odean, 2001, Boys will be Boys: Gender, Overconfidence, and Common Stock Investment, *Quarterly Journal of Economics*, 116, 261-292.

Chae, Joon, and Albert Wang, 2003, Who Makes Markets? Do Dealers Provide or Take Liquidity? working paper #4434-03, MIT, Cambridge, MA.

Coval, Joshua D., David Hirshleifer, and Tyler Shumway, 2003, Can Individual Investors Beat the Market, working paper, Harvard Business School, Cambridge, MA.

Garvey, Ryan, and Anthony Murphy, 2001, How Profitable Day Traders Trade: An Examination of Trading Profits, working paper, University College Dublin, Dublin, Ireland.

Harris, Jeffrey H., and Paul H. Schultz, 1998, The Trading Profits of SOES Bandits, *Journal of Financial Economics*, 50, 39-62.

Ivkovich and Weisbenner, 2005.

Ivkovich, Sialm, and Weisbenner, 2007.

Korniotis and Kumar, 2008.

Linnainmaa, Juhani, 2003, The Anatomy of Day Traders, working paper, UCLA, Los Angeles, CA.

Mahani and Bernhardt, 2007.

Odean, Terrance, 1998, Volume, Volatility, Price, and Profit When All Traders Are above Average, *Journal of Finance* 53, 1887-1934.

Odean, Terrance, 1999, Do Investors Trade too Much?, *American Economic Review*, 89, 1279-1298.

Seasholes, Mark and Guojun Wu, 2004, Profiting from Predictability: Smart Traders, Daily Price Limits, and Investor Attention, working paper, UC Berkeley.

Table 1: Gross and Net Abnormal Returns from Day Trading: 1992 to 2006

This table presents the daily percentage alpha from aggregate day trading and the remaining portfolio of day traders (i.e., positions held beyond one day). The alphas are estimated using the following regression of daily returns: $(R_{pt}-R_{ft})=\alpha_p+\beta_p(R_{mt}-R_{ft})+\varepsilon_{pt}$, where R_{pt}, R_{mt}, and R_{ft} are the portfolio return, market return, and riskfree return (respectively). The gross day trading return is calculated from daily round-trip trades plus the intraday returns on open trades; an open trade is a trade made during the day that results in an outstanding position at the close of the day. The net day trading return assumes a 10 bps round-trip commission and a 30 bps transaction tax on sales. The remaining portfolio return is the return earned on positions that remain open at the market close.

	Returns to Day Trading						Remaining Portfolio Return				Total Portfolio Return				
	Gross		Net												Day Trade /
	α (%)	*t-stat*	α (%)	t-stat	Beta	R-Sq	α (%)	*t-stat*	Beta	R-Sq	α (%)	*t-stat*	Beta	R-Sq	All Trade
ALL Years	-0.099	-12.38	-0.249	-31.30	0.29	42%	-0.014	-2.48	0.95	94%	-0.041	-7.51	0.90	94%	27.3%
1992	0.043	1.26	-0.053	-1.57	0.40	50%	-0.028	-0.80	1.12	88%	-0.048	-1.43	1.07	88%	10.6%
1993	-0.093	-3.03	-0.190	-6.24	0.36	56%	-0.056	-2.16	0.91	92%	-0.078	-3.12	0.87	92%	10.3%
1994	-0.135	-4.97	-0.273	-10.15	0.35	57%	0.016	0.64	0.82	90%	-0.006	-0.25	0.79	90%	21.7%
1995	-0.055	-2.21	-0.212	-8.66	0.27	44%	-0.026	-1.59	0.99	96%	-0.040	-2.51	0.95	96%	25.4%
1996	-0.099	-4.86	-0.241	-11.80	0.27	46%	-0.022	-1.29	0.85	92%	-0.038	-2.27	0.82	92%	22.5%
1997	-0.116	-3.67	-0.281	-8.95	0.28	38%	0.021	1.13	0.98	96%	-0.005	-0.29	0.93	95%	29.6%
1998	-0.087	-3.51	-0.259	-10.55	0.23	41%	-0.007	-0.56	0.93	98%	-0.031	-2.44	0.88	98%	29.9%
1999	-0.087	-2.70	-0.238	-7.45	0.29	44%	-0.004	-0.24	0.93	97%	-0.030	-1.98	0.89	97%	26.0%
2000	-0.047	-1.11	-0.210	-4.95	0.25	37%	-0.038	-2.11	0.95	98%	-0.070	-4.09	0.91	98%	27.8%
2001	-0.142	-3.32	-0.311	-7.28	0.27	39%	0.012	0.44	0.98	95%	-0.046	-1.69	0.91	95%	31.1%
2002	-0.166	-4.68	-0.329	-9.33	0.26	40%	0.008	0.38	0.99	96%	-0.041	-1.91	0.92	96%	29.1%
2003	-0.152	-5.65	-0.310	-11.66	0.25	39%	-0.015	-0.78	0.93	95%	-0.048	-2.65	0.87	94%	28.2%
2004	-0.112	-3.76	-0.272	-9.22	0.26	40%	-0.022	-1.16	0.89	95%	-0.047	-2.65	0.85	95%	27.8%
2005	-0.137	-6.49	-0.308	-14.79	0.33	40%	-0.002	-0.10	0.92	91%	-0.025	-1.61	0.88	90%	31.4%
2006	-0.141	-5.35	-0.306	-11.78	0.30	36%	0.018	1.00	0.89	91%	-0.005	-0.29	0.85	90%	30.1%

Table 2: Performance for Sorts based on Prior Year Day Trading Activity: 1993 to 2006

Day Traders are grouped based on prior year trading activity (e.g., "1 to 500" are the top 500 day traders from year t). The table presents the aggregate performance for each group in the year following ranking (t+1). The alphas are estimated using the following regression of daily returns: $(R_{pt}-R_{ft})=\alpha_p+\beta_p(R_{mt}-R_{ft})+\varepsilon_{pt}$, where R_{pt}, R_{mt}, and R_{ft} are the portfolio return, market return, and riskfree return (respectively). The gross day trading return is calculated from daily round-trip trades plus the intraday returns on open trades; an open trade is a trade made during the day that results in an outstanding position at the close of the day. The net day trading return assumes a 10 bps round-trip commission and a 30 bps transaction tax on sales. The remaining portfolio return is the return earned on positions that remain open at the market close. "Day Trade / All Trade" is the fraction of the groups trading that is round-trip day trades. The total portfolio return combines the net day trading return and the remaining portfolio return with alphas calculated relative to the close-to-close market return. The last two columns present the share of total market day trading and all trading accounted for by each group.

	Returns to Day Trading						Remaining Portfolio Return				Total Portfolio Return					Share of
	Gross		Net												Day Trade /	Day
	α (%)	*t-stat*	α (%)	t-stat	Beta	R-Sq	α (%)	*t-stat*	Beta	R-Sq	α (%)	*t-stat*	Beta	R-Sq	All Trade	Trading
1 to 500	0.131	17.28	-0.068	-9.02	0.20	30%	0.010	1.41	0.97	91%	-0.022	-3.11	0.89	91%	42.8%	10.0%
501 to 1,000	0.049	6.52	-0.142	-18.84	0.21	33%	0.006	0.78	0.95	91%	-0.027	-3.96	0.89	91%	39.9%	4.6%
1,001 to 2,000	0.003	0.39	-0.177	-22.50	0.23	35%	0.001	0.21	0.94	93%	-0.032	-5.21	0.88	93%	35.6%	5.7%
2,001 to 5,000	-0.046	-5.88	-0.221	-28.03	0.25	38%	-0.004	-0.61	0.94	94%	-0.037	-6.44	0.88	94%	33.7%	9.5%
5,001 to 10,000	-0.091	-11.36	-0.259	-32.35	0.26	40%	-0.008	-1.45	0.93	94%	-0.041	-7.30	0.88	94%	31.3%	8.8%
10,001 to 20,000	-0.122	-14.98	-0.282	-34.76	0.28	42%	-0.009	-1.63	0.93	95%	-0.041	-7.79	0.88	95%	28.6%	10.1%
20,001 to 50,000	-0.148	-17.68	-0.296	-35.56	0.29	43%	-0.015	-3.05	0.92	95%	-0.044	-9.05	0.88	95%	25.0%	14.0%
> 50000	-0.156	-18.20	-0.291	-34.15	0.30	44%	-0.015	-3.03	0.94	96%	-0.039	-8.12	0.90	96%	21.4%	27.9%
No Prior Yr Rank	-0.149	-16.87	-0.297	-33.92	0.30	41%	-0.018	-2.44	0.97	91%	-0.056	-7.91	0.91	91%	27.5%	9.3%

Table 3: Performance for Sorts based on Past Day Trading Profits: 1993 to 2006

Day Traders are grouped based on prior year daily Sharpe ratio for only day trading (e.g., "1 to 500" are the top 500 day traders from year t).. The table presents the aggregate performance for each group in the year following ranking (t+1). The alphas are estimated using the following regression of daily returns: $(R_{pt}-R_{ft})=\alpha_p+\beta_p(R_{mt}-R_{ft})+\varepsilon_{pt}$, where R_{pt}, R_{mt}, and R_{ft} are the portfolio return, market return, and riskfree return (respectively). The gross day trading return is calculated from daily round-trip trades plus the intraday returns on open trades; an open trade is a trade made during the day that results in an outstanding position at the close of the day. The net day trading return assumes a 10 bps round-trip commission and a 30 bps transaction tax on sales. The remaining portfolio return is the return earned on positions that remain open at the market close. "Day Trade / All Trade" is the fraction of the groups trading that is round-trip day trades. The total portfolio return combines the net day trading return and the remaining portfolio return with alphas calculated relative to the close-to-close market return. The last two columns present the share of total market day trading and all trading accounted for by each group.

	Returns to Day Trading						Remaining Portfolio Return				Total Portfolio Return					Share of
	Gross		Net												Day Trade /	Day
	α (%)	*t-stat*	α (%)	t-stat	Beta	R-Sq	α (%)	*t-stat*	Beta	R-Sq	α (%)	*t-stat*	Beta	R-Sq	All Trade	Trading
1 to 500	0.495	71.69	0.281	41.44	0.20	35%	0.011	1.80	0.84	92%	0.020	3.48	0.79	92%	45.8%	1.7%
501 to 1,000	0.322	41.72	0.133	17.56	0.19	28%	0.015	2.11	0.83	90%	0.012	1.89	0.78	90%	35.3%	1.3%
1,001 to 2,000	0.233	30.22	0.059	7.72	0.20	30%	0.009	1.33	0.82	89%	0.002	0.36	0.77	89%	30.7%	2.0%
2,001 to 4,000	0.158	20.58	-0.006	-0.83	0.21	33%	0.004	0.62	0.83	90%	-0.007	-1.10	0.78	90%	28.3%	3.1%
4,001 to 6,000	0.097	12.29	-0.061	-7.74	0.23	34%	0.000	-0.08	0.87	92%	-0.016	-2.60	0.82	92%	26.3%	2.5%
6,001 to 8,000	0.049	6.10	-0.105	-13.05	0.24	35%	-0.003	-0.51	0.87	92%	-0.020	-3.43	0.83	92%	25.9%	2.1%
8,001 to 10,000	0.016	1.99	-0.138	-16.97	0.25	36%	-0.008	-1.22	0.90	92%	-0.028	-4.57	0.85	92%	25.6%	1.9%
> 10,000	-0.175	-21.58	-0.342	-42.36	0.29	43%	-0.017	-3.16	0.95	95%	-0.057	-10.77	0.90	95%	31.6%	51.5%
No Prior Yr Rank	-0.162	-18.11	-0.269	-30.16	0.30	42%	-0.004	-0.69	0.93	95%	-0.039	-7.47	0.87	95%	13.5%	33.9%

Table 4: Performance for Sorts based on Prior Year Order Type: 1993 to 2006

Day Traders are grouped into deciles based on the aggressiveness of prior year orders. The extreme deciles are further split in two. The table presents the aggregate performance for each group in the year following ranking (t+1). The alphas are estimated using the following regression of daily returns: $(R_{pt} - R_{ft}) = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \varepsilon_{pt}$, where Rpt, Rmt, and Rft are the portfolio return, market return, and riskfree return (respectively). The gross day trading return is calculated from daily round-trip trades plus the intraday returns on open trades; an open trade is a trade made during the day that results in an outstanding position at the close of the day. The net day trading return assumes a 10 bps round-trip commission and a 30 bps transaction tax on sales. The remaining portfolio return is the return earned on positions that remain open at the market close. "Day Trade / All Trade" is the fraction of the groups trading that is round-trip day trades. The total portfolio return combines the net day trading return and the remaining portfolio return with alphas calculated relative to the close-to-close market return. The last two columns present the share of total market day trading and all trading accounted for by each group.

	Returns to Day Trading						Remaining Portfolio Return				Total Portfolio Return					Share of
	Gross		Net												Day Trade /	Day
	α (%)	*t-stat*	α (%)	t-stat	Beta	R-Sq	α (%)	*t-stat*	Beta	R-Sq	α (%)	*t-stat*	Beta	R-Sq	All Trade	Trading
Passive (1a)	-0.054	-6.90	-0.163	-21.35	0.27	42%	0.000	-0.01	0.93	96%	-0.008	-1.62	0.89	96%	12.1%	1.1%
1b	-0.117	-14.31	-0.230	-28.40	0.28	43%	-0.005	-0.94	0.92	95%	-0.023	-4.69	0.88	95%	13.4%	1.4%
2	-0.130	-15.77	-0.247	-30.30	0.28	42%	-0.011	-2.07	0.90	95%	-0.032	-6.64	0.86	95%	14.8%	3.5%
3	-0.130	-15.52	-0.252	-30.37	0.28	42%	-0.010	-1.88	0.90	94%	-0.035	-6.66	0.86	94%	16.6%	4.8%
4	-0.117	-14.03	-0.244	-29.42	0.28	41%	-0.011	-1.87	0.89	94%	-0.035	-6.45	0.85	94%	18.4%	6.1%
5	-0.110	-13.34	-0.243	-29.53	0.28	41%	-0.011	-1.73	0.90	93%	-0.038	-6.43	0.86	93%	20.6%	7.6%
6	-0.102	-12.42	-0.242	-29.58	0.27	41%	-0.006	-1.03	0.92	93%	-0.037	-6.23	0.87	93%	23.4%	9.8%
7	-0.099	-12.09	-0.246	-30.07	0.27	41%	-0.008	-1.42	0.94	95%	-0.043	-8.03	0.88	94%	25.9%	11.6%
8	-0.106	-12.77	-0.258	-31.03	0.28	41%	-0.007	-1.19	0.96	95%	-0.048	-8.82	0.89	94%	27.6%	12.6%
9	-0.129	-15.09	-0.285	-33.17	0.29	42%	-0.007	-1.28	0.98	95%	-0.056	-10.70	0.91	95%	28.9%	12.3%
10b	-0.163	-18.09	-0.320	-35.52	0.31	42%	-0.013	-2.29	1.00	95%	-0.068	-12.77	0.93	95%	29.9%	5.6%
Aggressive (10a)	-0.193	-20.24	-0.343	-35.91	0.33	43%	-0.018	-3.30	1.02	96%	-0.076	-14.22	0.95	95%	28.5%	4.4%
No Prior Yr Rank	-0.164	-18.55	-0.279	-31.79	0.30	42%	0.001	0.23	0.95	94%	-0.042	-7.16	0.87	93%	17.2%	19.4%

Table 5: Logistic Regressions of Positive Profit Probability

A profit dummy takes a value of one if the net profits from day trading for an investor are positive in year t . The probability of a positive profit is estimated using a logistic regression where the dependent variable is the profit dummy. Independent variables for each investor include the Sharpe ratio of past day trading profits and day trading returns, the percent of trading in concentrated in the top stock, the fraction of trading devoted to day trading, and dummy variables for the cumulative number of days of day trading and the cumulative volume of day trading. All independent variables are cumulative through year t-1. The regression is limited to day traders with a minimum total value of trade $NT 600,000 in the year that profitability is measured. The probability impact is measured as the change in probability from a baseline model. The baseline model sets all dummy variables to zero. For continuous variables, the probability change is based on moving from the 25th to 75th percentile of the distribution of the independent variable. For dummy variables, the probability change is based on moving from zero to one. Remaining continuous variables are set to their mean, while remaining dummy variables are set to zero.

Table 5: Cont'd

	Intercept	Sharpe Profit	Sharpe Return	Percent Top Stock	Percent Short	Fraction Day Trades	Fraction Agg. Trades	No. of Prior Days with Day Trading 5-20	21-70	71-300	> 300	Volume of Prior Day Trading ($NT Mil) 0.9-9	9-45	45-270	> 270
Variable Mean	0.866	-0.084	-0.136	0.158	0.091	0.150	0.723	0.203	0.244	0.207	0.069	0.236	0.258	0.206	0.081
Probability Impact		6.1%	3.1%	0.5%	0.5%	0.0%	0.1%	-1.1%	-2.8%	-4.2%	-4.8%	4.0%	5.6%	8.0%	12.0%
							Coefficient Estimates								
Mean	-1.47	4.53	1.23	0.27	0.33	0.14	0.06	-0.10	-0.27	-0.43	-0.50	0.31	0.42	0.57	0.80
Std. Error	0.05	0.19	0.11	0.04	0.05	0.08	0.05	0.01	0.01	0.03	0.07	0.05	0.05	0.05	0.06
1994	-1.50	2.79	0.74	0.20	0.14	0.09	0.14	-0.23	-0.34	-0.31	-0.33	-0.04	0.14	0.35	0.42
1995	-1.38	4.76	0.61	0.51	0.31	-0.24	0.19	-0.11	-0.29	-0.34	-0.14	0.05	0.11	0.28	0.42
1996	-1.43	5.40	0.76	0.47	0.25	-0.01	0.22	-0.17	-0.35	-0.49	-0.35	0.17	0.30	0.51	0.78
1997	-2.02	4.97	0.88	0.26	0.36	0.04	0.39	-0.13	-0.27	-0.42	-0.43	0.45	0.61	0.82	1.17
1998	-1.61	4.52	0.88	0.27	0.26	-0.24	0.07	-0.04	-0.22	-0.35	-0.37	0.30	0.42	0.64	0.93
1999	-1.48	4.45	1.14	0.00	0.13	-0.19	0.29	-0.09	-0.23	-0.38	-0.39	0.57	0.68	0.81	1.11
2000	-1.19	3.82	1.51	0.15	0.32	0.06	-0.03	-0.07	-0.18	-0.27	-0.27	0.41	0.46	0.50	0.71
2001	-1.48	3.91	1.47	0.17	0.12	0.06	0.08	-0.07	-0.22	-0.35	-0.41	0.49	0.60	0.69	0.84
2002	-1.54	4.37	1.69	0.35	0.78	0.23	-0.13	-0.08	-0.25	-0.42	-0.47	0.23	0.33	0.41	0.71
2003	-1.50	4.72	1.79	0.45	0.50	0.48	-0.09	-0.05	-0.30	-0.54	-0.70	0.30	0.41	0.59	0.80
2004	-1.29	5.16	1.49	0.23	0.31	0.18	-0.08	-0.08	-0.31	-0.53	-0.81	0.50	0.61	0.78	1.01
2005	-1.42	5.38	1.30	0.28	0.22	0.58	-0.16	-0.07	-0.30	-0.61	-1.04	0.32	0.40	0.56	0.83
2006	-1.31	4.60	1.71	0.13	0.54	0.74	-0.10	-0.09	-0.29	-0.53	-0.83	0.31	0.38	0.50	0.61

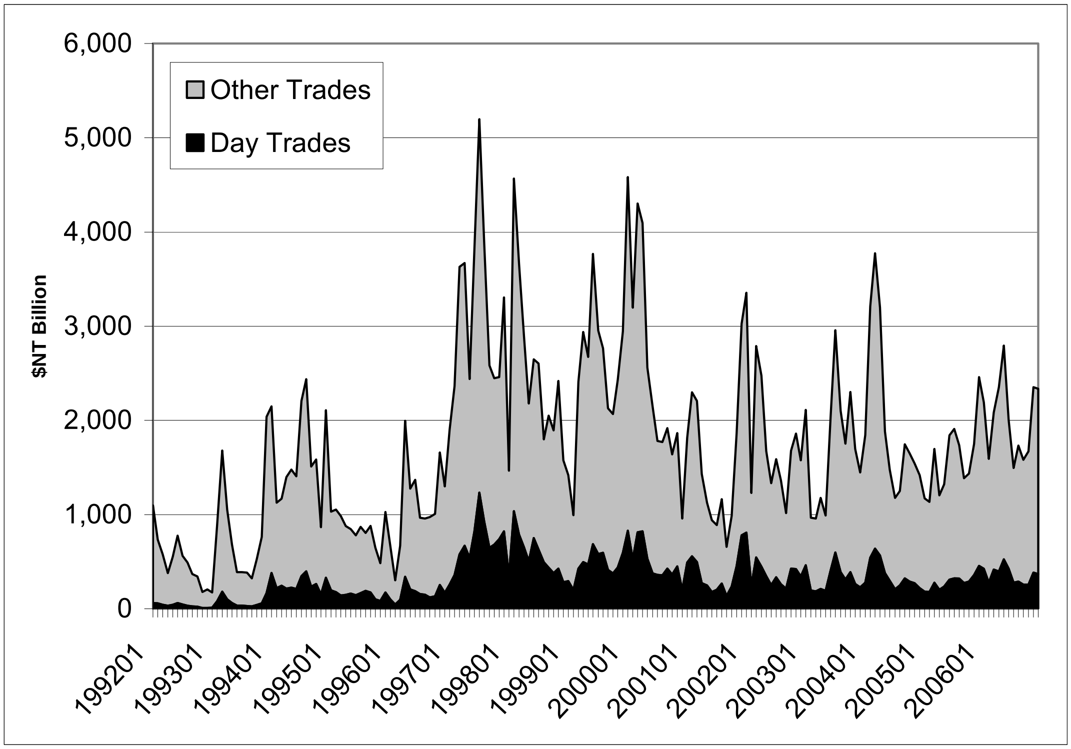

Figure 1: **Total Trading and Day Trading in Taiwan: 1991 to 2006**
Day trading is defined as the purchase and sale of the same stock on the same day by the same investor.

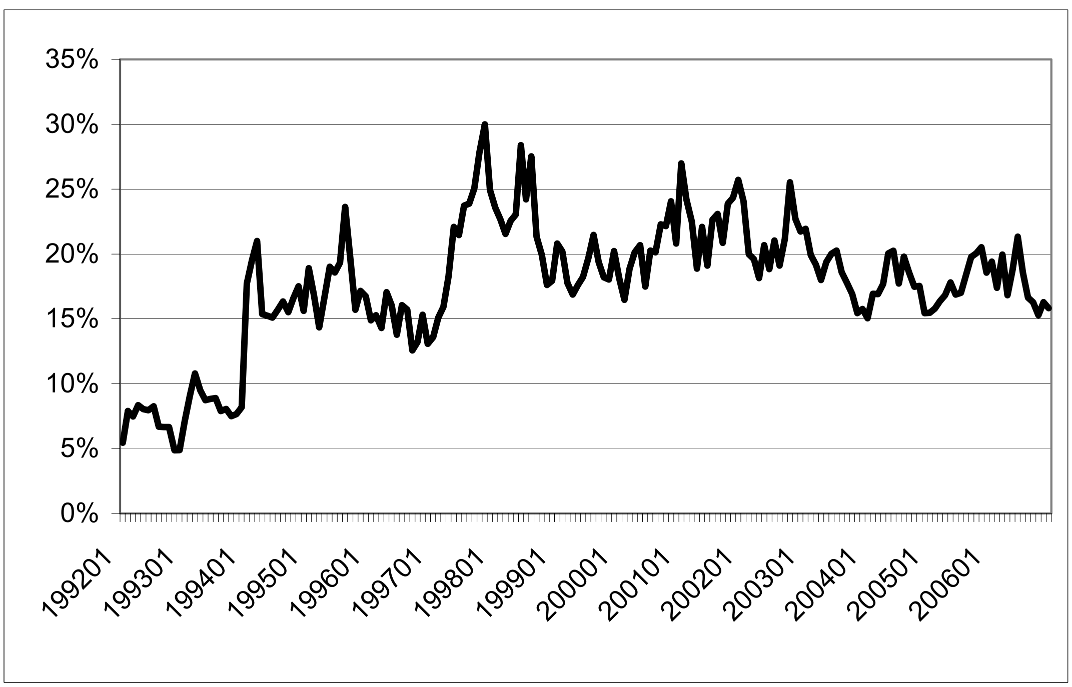

Figure 2: Day Trading as a Percent of Total Volume

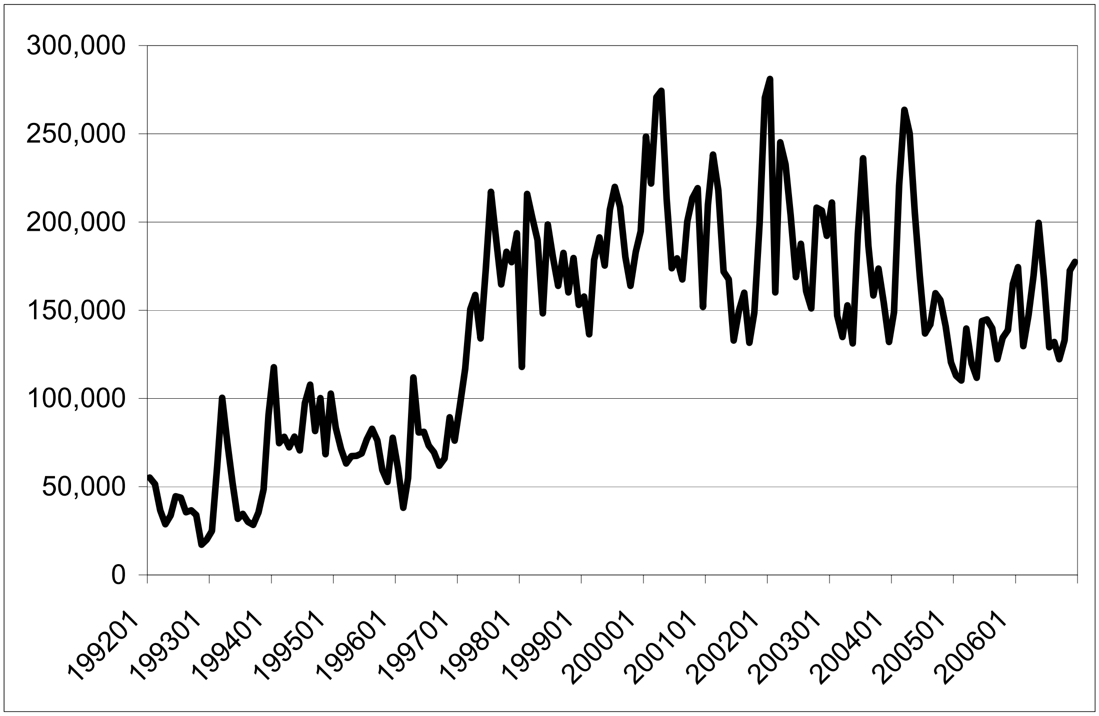

Figure 3: Number of Individual Day Traders by Month

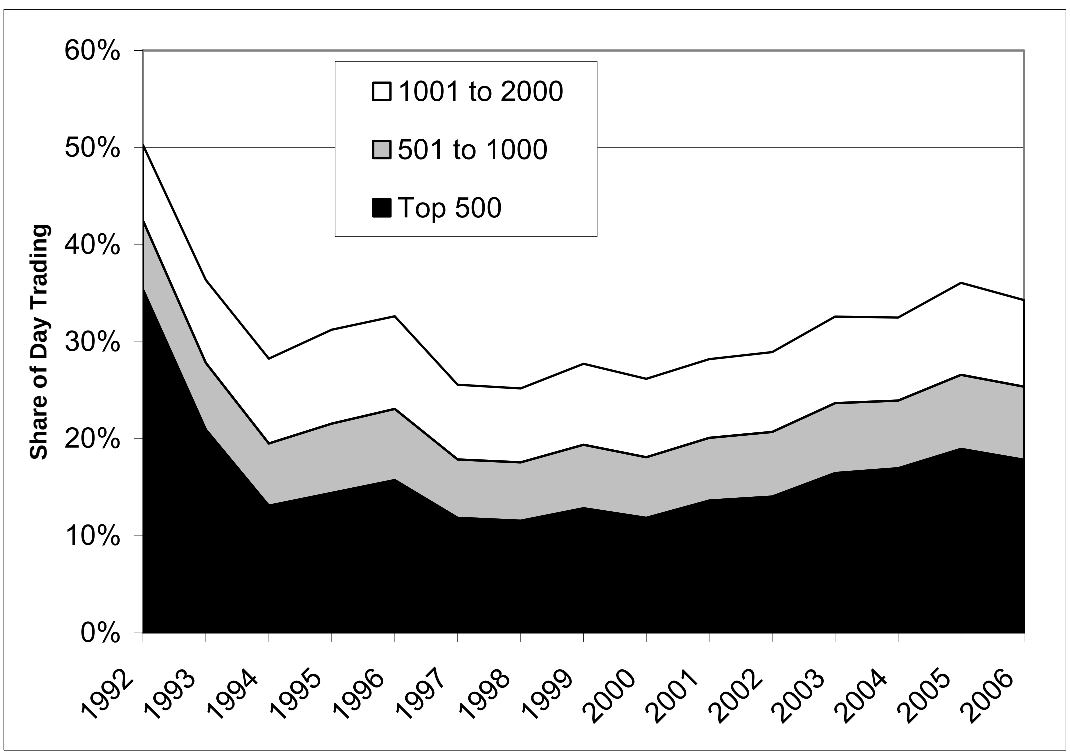

Figure 4: Concentration of Day Trading

Day Traders are ranked by year based on total day trading volume. The graph presents the share of all day trading traced to the top 2000 day traders.

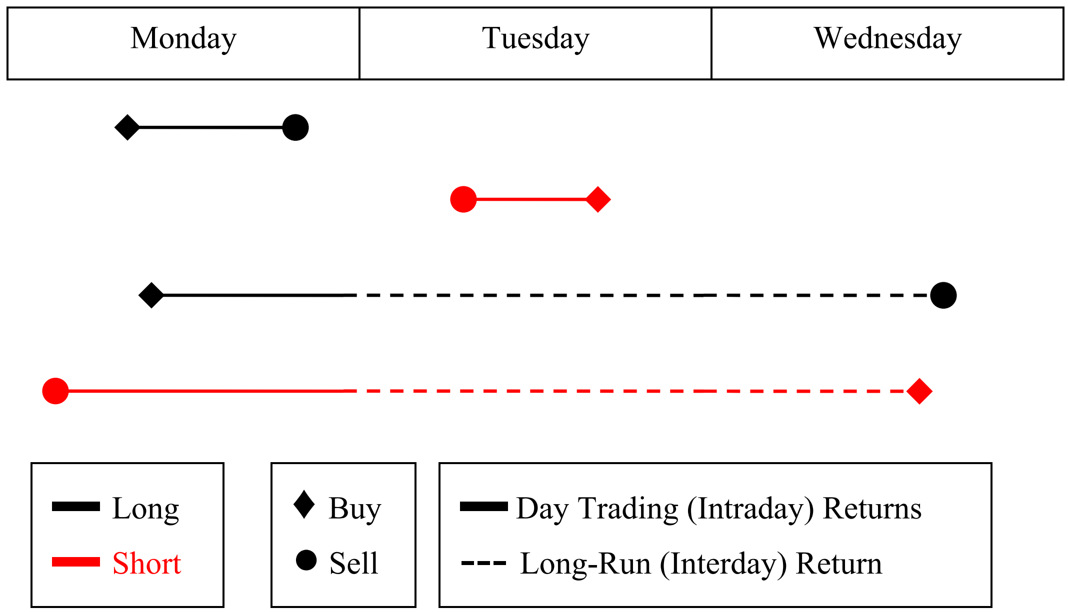

Figure 5: Example of Trading Activity for a Day Trader

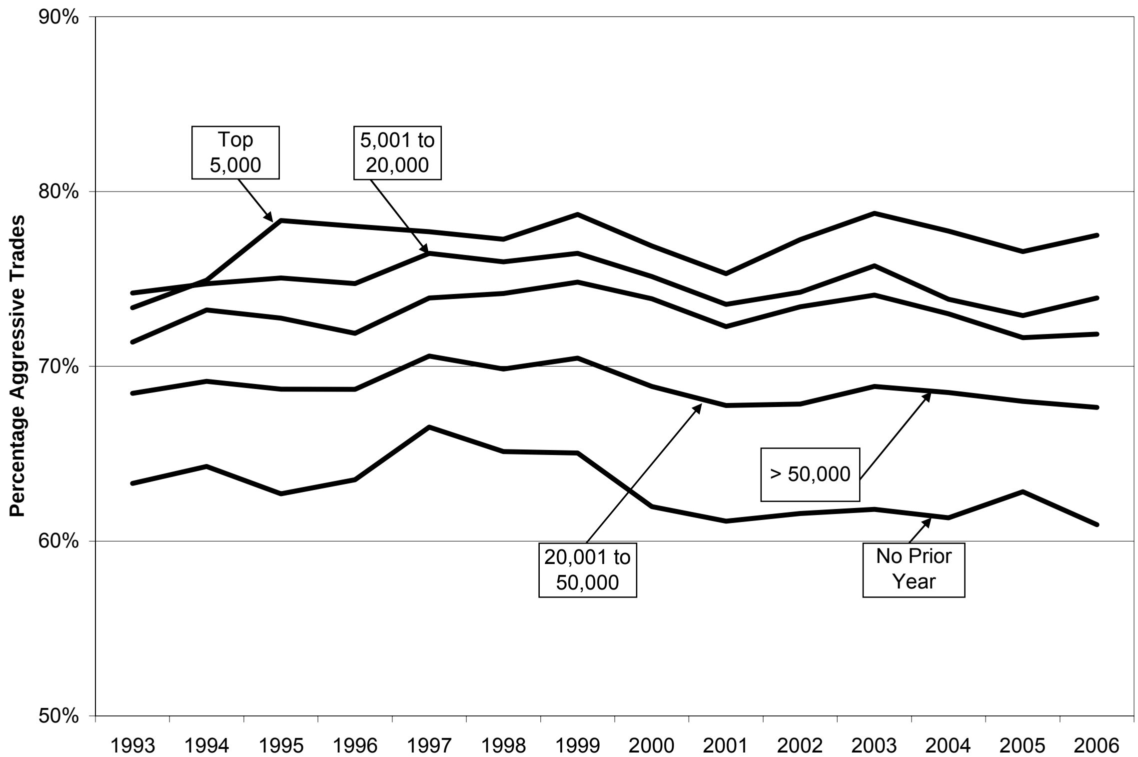

Figure 6: Percentage Aggressive Trades by Categories of Day Trading Intensity