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Journal of Financial Markets 18 (2014) 1–24

Journal of FINANCIAL MARKETS

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The cross-section of speculator skill: Evidence from day trading ☆

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Received 15 August 2011; received in revised form 9 May 2013; accepted 13 May 2013
Available online 2 July 2013

Abstract

We document economically large cross-sectional differences in the before- and after-fee returns earned by speculative traders by analyzing day traders in Taiwan from 1992 to 2006. We sort day traders based on their returns in year *y* and analyze their performance in year *y*+1; the 500 top-ranked day traders go on to earn *daily* before-fee (after-fee) returns of 61.3 (37.9) bps per day; bottom-ranked day traders go on to earn daily before-fee (after-fee) returns of −11.5 (−28.9) bps per day. Less than 1% of the day trader population is able to predictably and reliably earn positive abnormal returns net of fees.

JEL classification: D14; G02

Keywords: Speculative trading; Day traders; Individual investors; Investor performance

☆We are grateful to the Taiwan Stock Exchange for providing the data used in this study. Barber appreciates the National Science Council of Taiwan for underwriting a visit to Taipei, where Timothy Lin (Yuanta Core Pacific Securities) and Keh Hsiao Lin (Taiwan Securities) organized excellent overviews of their trading operations. We have benefited from the comments of seminar participants at Oregon, Utah, Virginia, Santa Clara, Texas, Texas A&M, Washington University, Peking University, and HKUST. Yu-Jane Liu and Yi-Tsung Lee acknowledge NSFC (71172026, 71021001, and 71172025) for financial support.
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1386-4181/$ - see front matter
http://dx.doi.org/10.1016/j.finmar.2013.05.006

1. Introduction

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 United States 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 et al. (2009), using complete transaction data for the Taiwan market from 1995 to 1999, document that the aggregate losses of individual investors exceed 2% of annual Gross Domestic Product in Taiwan.

Recent research documents that a host of variables (e.g., IQ, cognitive abilities, geography, portfolio concentration, age, and past performance) reliably predict cross-sectional variation in performance.[4] But even the most skilled stock pickers in these studies are unable to deliver a return that covers a reasonable accounting for transaction costs. Thus, it remains an open question whether some individual investors can profit from speculative trading.

Prior studies almost certainly underestimate the economic significance of cross-sectional variation in the skill of individual investors. Virtually all prior studies of ability have analyzed the general population of individual investors, who tend to be infrequent traders. This underestimates the variation in cross-sectional ability of investors, since a large proportion of trades by infrequent traders will have non-speculative motives (e.g., diversification, rebalancing, tax, or liquidity motivations). In addition, many prior studies of cross-sectional variation in skill have relied on data from a single broker (see footnote 4).

We are able to enrich this prior evidence by analyzing the returns earned by all speculators in an entire market over a 15-year period. As in Barber et al. (2009), we use complete transaction data for the Taiwan stock market, but use a much longer sample period of 1992–2006. Barber et al. (2009) analyze the aggregate performance of individual investors and document that individual investors incur systematic and economically large trading losses. In contrast, we focus on the variation in performance across traders.

To analyze the cross-sectional of investor performance, we focus on day trading for three reasons. First, as we discuss in detail, day traders are an important equilibrium feature in Taiwan and account for 17% of all volume on the Taiwan Stock Exchange (TSE) during our sample period. Second, we are interested in analyzing the cross-section of speculator skill, and day traders, given their short holding period, are almost certainly speculators. Third, the signal-to-noise ratio regarding investor skill arguably is greater for day traders than for investors with longer holding periods. Several prior studies document that the lion's share of abnormal returns earned around an informed trade occurs immediately following the trade (e.g., Coval et al., 2005; Barber et al., 2009; Grinblatt et al., 2012). If so, returns on the day of trade may better separate skilled and unskilled investors than long-run returns. Furthermore, because day traders trade frequently, we observe outcomes of many trading decisions for each investor, which is likely to lead to a more precise estimate of the investor's skill.

[4]See Ivkovic and Weisbenner (2005), Coval et al. (2005), Ivkovic et al. (2008), Kumar (2009), Korniotis and Kumar (2011, 2013), and Grinblatt et al. (2012). Korniotis and Kumar (2013) document that smart individual investors reliably outperform dumb individual investors; however, smart investors are unable to beat passive benchmarks after accounting for transactions costs. All of these studies use data from a large discount broker with the exception of Grinblatt et al. (2012). Grinblatt and Keloharju (2000) also document poor performance by individual investors. See Barber and Odean (2012) for a comprehensive review of the performance of retail traders.

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 open positions for the five days following a trade. The day trading return includes both round-trip and one-sided trades (i.e., trades that result in an open position at the close of trading). The open positions capture the returns to all positions that remain open after the day of trade.

Consistent with prior work on the performance of individual investors, the vast majority of day traders lose money. In the average year during our 1992–2006 sample period, about 450,000 Taiwanese individuals engaged in day trading. Among thousands of occasional day traders in the average year, 277,000 individuals engaged in day trades in excess of $NT 600,000 per year (about $US 20,000)[5] and about 20% of these day traders earn positive abnormal returns net of fees (commissions and transaction taxes).[6] Of course, some outperformance would be expected by sheer luck.

But luck is not the whole story. Our main result documents the presence of statistically and economically large cross-sectional variation in trader ability. In the average year, about 4,000 day traders are able to predictably profit net of a reasonable accounting for transactions costs. Specifically, we sort investors into groups based on their day trading returns in year y and analyze the performance of each group in year $y+1$. We document that only the 4,000 most profitable day traders (less than 1% of the total population of day traders) from the prior year go on to earn reliably positive abnormal returns net of trading costs in the subsequent year. But, the stock picking ability of these investors is remarkable. The top 500 day traders (based on prior year ranking) earn gross (net) abnormal returns of 61.3(37.9) bps *per day* on their day trading portfolio, while the tens of thousands of day traders with a history of losses in the prior year go on to earn gross (net) abnormal returns of -11.5 (-28.9) bps *per day*.

Two points are worth emphasizing in these results. First, the spread in gross returns between the top and bottom performing investors at 73 bps per day is enormous when compared to most other studies of cross-sectional ability in investor performance. For example, using data from Finland, Grinblatt et al. (2012) document that the buys of high IQ investors outperform those of low IQ investors by 4.4 bps per day in the days immediately following the purchase. Using data from a large U.S. discount broker, Coval et al. (2005) document that a strategy long firms purchased by previously successful investors and short firms purchased by previously unsuccessful investors earns a daily abnormal return of 5 bps before trading costs (assuming a holding period of one day). We believe that the much larger returns that we document are a result of our focus on frequent traders, who are almost certainly speculators and among whom we are better able to identify skilled investors.

Second, to our knowledge, we provide the only study of individual investor performance that documents that savvy investors are able to cover a reasonable estimate of trading costs. The top 500 day traders (based on prior year ranking) are able to cover rather large transaction costs (on top of commissions and spreads, Taiwan charges a 30 bps tax on sales) and earn an impressive net return ranging from 24.1 bps (assuming a statutory maximum commission of 14.25 bps one way) to37.9 bps per day (assuming heavily discounted commissions of 5 bps one way) on the day of trade.

[5]The mean TWD/USD exchange rate from 1992 to 2006 was 30.54 with a low of 24.65 and a high of 35.01.

[6]The percentage of day traders who earn positive intraday returns net of transaction costs in a year varies between 17% and 20% depending on how we define the population of day traders (e.g., requiring minimum number of days of trading or minimum value of trading).

In auxiliary analyses, we explore factors that might explain the remarkable profitability of a select group of day traders. We find some evidence that profitable day traders either use private information (or respond early to public information). Specifically, the returns of profitable day traders are higher in hard-to-value stocks (e.g., small or volatile stocks) and in periods around earnings announcements. In contrast, day traders with systematic losses also incur losses in hard-to-value stocks and around earnings announcements. In combination, these results suggest that day traders forecast short-term price movements in stocks or periods with high levels of information asymmetry.

We also test the hypothesis that day traders profit by serving as liquidity providers on the Taiwan Stock Exchange, which is a pure electronic limit order market. If so, day traders would be compensated for serving as the counterparty to uninformed traders who demand immediacy. Using the orders underlying executed trades, we document that day traders tend to place aggressive orders that demand immediacy; the most profitable day traders tend to lean somewhat more on passive orders, but even for this select group of profitable day traders, nearly two-thirds of trades emanate from aggressive orders. Furthermore, the aggressiveness of orders underlying trades is an economically weak predictor of future day trader profitability. These empirical observations are not consistent with the hypothesis that liquidity provision is the main driver of the strong returns earned by a select group of successful day traders.

Finally, we investigate the characteristics of profitable day traders. Past performance (either returns or dollar profits) is, by a large margin, the best predictor of future performance. Aside from past performance, the most important predictor of future performance is the concentration of trading in a few stocks, which is consistent with the hypothesis that successful day traders focus on a few stocks in an attempt to garner an informational advantage in those stocks.

In addition to providing insights on the cross-sectional variation in investor performance, ours also is among the first studies of day trading in financial markets. In Taiwan, 17% of all trading volume can be traced to round-trip day trades made by individual investors. This trading activity is remarkably stable over the 15-year period that we analyze, despite the poor performance profile of day traders. Day trading is clearly an equilibrium feature of the TSE.

The rest of this paper is organized as follows. We survey related research in Section 1. We discuss Taiwan market rules, our dataset, and methods in Section 2. We present results in Section 3, followed by a discussion in Section 4 and concluding remarks in Section 5.

2. Background and related research

Our study is the first large-scale study of day trading for an entire market. However, we are not the first to study day trading. Four 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 (2005a) analyze the trading of 96,000 trades made by 15 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 15 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. Garvey and Murphy (2005b) find similar results in a follow-up study of 1,386 day traders over two months. Both of the studies by Garvey and Murphy analyze only round-trip trades, which is likely to bias performance measurement positively as traders are more likely to close out winning positions. Seasholes and Wu (2007) 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 (2005a). 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). In a closely related paper, Linnainmaa (2005) analyzes the disposition effect in day traders and its effect on performance. Linnainmaa (2003, 2005) reports that the net returns of these investors are similar to those of a control sample, but he does not analyze the cross-sectional variation in day trader performance in either paper (the focus of our analysis). In a follow-up paper, Linnainmaa (2011) uses a sample of frequent traders in Finland to test learning models of speculative trading. He concludes “investors trade to learn even if they are pessimistic about their ability”. Barber, Lee, Liu, and Odean (2011) examine learning among Taiwanese day traders and conclude that, while learning takes place, it is slow, suboptimal, and costly. In our analysis, we focus on

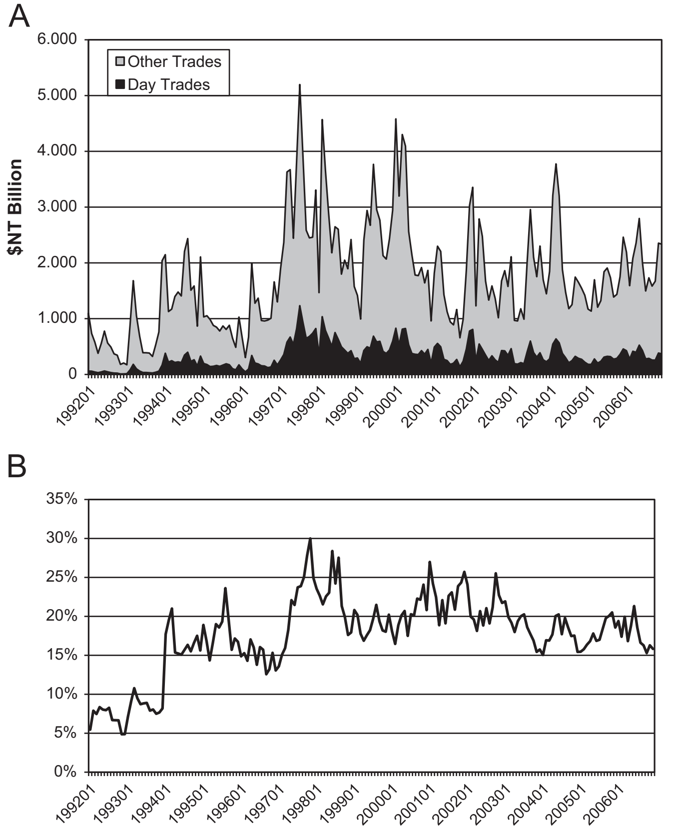

Fig. 1. Day trading in Taiwan: 1992–2006. Day trading is defined as the purchase and sale of the same stock on the same day by the same investor. (a) Panel A: Day trading volume and total volume, (b) Panel B: Percentage of volume by day traders.

cross-sectional differences in ability and do not address the question of whether investors rationally learn.

In contrast to the small-scale studies of day trading, we provide a comprehensive analysis of the profitability of all day trading in Taiwan over a 15-year period. To do so, we use a unique and remarkably complete dataset that contains the entire transaction data, underlying order data, and the identity of each trader on the TSE. In total, the dataset contains 3.7 billion two-sided transactions with a value of $NT 310 trillion (approximately $10 trillion U.S.). 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. In the average year of our sample, 450,000 individual investors engage in day trading, and their day trading accounts for 17% of all volume on the TSE (Fig. 1). Virtually all day trading can be traced to individual investors in Taiwan. In a typical month, 15% of individual investors who trade on the TSE engage in at least one day trade.

3. The Taiwan market, data, and methods

3.1. Taiwan market rules

Before proceeding, it is useful to describe the TSE. The TSE operates in a consolidated limit order book environment in which only limit orders are accepted. During the regular trading session, from 9 am to noon (or 1:30 pm after 2001), buy and sell orders can interact to determine the executed price subject to applicable automatching rules.[7] 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 or 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 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 orders to obtain matching priority. Prior to 2002, there is a daily price limit of 7% in each direction and a trade-by-trade intraday price limit of two ticks from the previous trade price.[8] After 2002, there is a temporary trading halt when the current price deviates by more than 3.5% from the last traded price.

Since our analysis focuses on day trading, an important consideration is transaction costs. Taiwan imposes a transaction tax on stock sales of 0.3%. When calculating net returns, we apply the 30 bps transaction tax to all sales.

Unfortunately, we do not know the commission paid on each trade, but from discussions with TSE officials, we know that commissions range from a low of about 5 bps to a maximum of 14.25 bps (one way). The TSE caps commissions at 0.1425% of the value of a trade, and this cap was the same throughout our sample period (1992–2006). Some brokers offer lower commissions for larger traders. Preferred traders can get heavy discounts on commissions—as

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

[8] From 2002 on, intraday price limit has been replaced by a temporarily trading interruption when the current price falls out of a specified range (±3.5%) of the last traded price.

low as 5 bps. We interviewed officials at brokerage firms and the TSE, who indicated that the trade-weighted average commission paid by all market participants is approximately 10 bps. These estimates are confirmed in press reports discussing commissions on the TSE. We present results based on the most heavily discounted commissions (5 bps).[9] Obviously, this overestimates the actual returns earned by some investors who face higher commissions. For most investors, we document negative net returns and the 5 bps commission assumption underestimates their losses. These investors certainly lose money regardless of the commission assumption. For the small group of investors who earn positive abnormal returns net of fees, we test the sensitivity of our results by also assuming commissions of 14.25 bps (the statutory maximum).

3.2. 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 categorize traders broadly as individuals, corporations, dealers, foreign investors, and mutual funds. The majority of investors (by value and number) are individual investors. Corporations include Taiwanese corporations and government-owned firms (e.g., the government-owned post, banking, and insurance services). Dealers include Taiwanese financial institutions such as Fubon Securities, Yuanta Core Pacific Securities, and Polaris 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 of which is ING Asset Management with $NT 163 billion invested in Taiwanese stocks in December 2006.

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 ($1/2 * P_b * \min(S_b,\ S_s) + 1/2 * P_s * \min(S_b, S_s)$). Over our sample period, day trading accounted for more than 17% of the total dollar value of trading volume. Most day trading (about two-thirds) 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 some cases (about a third of all day trading), investors purchase (or short) a stock and later the same day sell (or buy to cover) only part of their initial position.

In Fig. 1, Panel A, we plot day trading (black) and other trading (gray). 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). In Fig. 1, Panel B, we plot the percentage of total volume that can be attributed to day trading. Over the full sample period, day trading represents 17% of total volume and the percentage is fairly stable over the last decade of our sample period. Though not

[9] According to the *United Night Daily Journal* (http://www.haixiainfo.com.tw/56439.html), commissions ranged from 6.25 bps to 12.25 bps. According to the *Apple Daily* (http://tw.nextmedia.com/applenews/article/art_id/3183148/IssueID/20070116) commission rates were 4.25 bps before 2007 for high volume traders. Bloggers provide similar accounts of heavily discounted commissions (http://blog.udn.com/ines0819/3122885 and http://cutiemaggie.pixnet.net/blog/post/26673014). Brokerage and exchange officials indicate discounting practices were common and consistent during our sample period.

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 changes in day trading on past returns (alternatively at monthly, quarterly, or annual horizons) and find past returns have no ability to predict changes in day trading.

Virtually all day trading can be traced to individual investors. In the average month, individual investors account for 95% of day trading. Individuals and corporations are free to short sell, although 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. dealers, dealers in Taiwan are not active providers of liquidity. Though dealers are required to adjust the demand and supply in the market efficiently 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 (2009) also report that TSE dealers are not net providers of liquidity. In the remainder of the paper, we restrict our analysis to individual investors.

3.3. *Performance measurement*

Our performance measurement focuses primarily on the intraday profits of all trades made by day traders and on trade-weighted intraday returns. Our return calculations assume that the value of trades represents the trader's capital at risk. This assumption yields returns that are of the correct sign, but are understated in absolute value for two reasons. First, investors who make sequential round-trip trades (e.g., a round-trip in stock A followed by a round-trip in stock B) do not need the total capital required to initiate positions in each stock. Second, investors may borrow to trade in margin accounts. 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.

We first calculate the intraday returns to day trading. To do so, we identify all trades made by day traders. We define a day trader as an investor who buys and sells the same stock on the same day during year y. We then analyze the performance of day traders in year $y+1$. To measure performance in year $y+1$, we calculate the profits on round-trip day trades and other trades that remain open at the close of the trading day. The other trades are either purchases to open a long position or sales to 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 (i.e., mark-to-market at the day's closing price). To calculate the daily return earned by a day trader, we sum the proceeds from stocks sold to close long positions and bought to close short positions (or their mark-to-market equivalent at the close of the trading day) and divide by the cost of initiating the position (i.e., the value of stocks bought or sold short at the time of the purchase or sale). We refer to this return as the gross return from day trading. To calculate the net return to day trading, we assume a 5 bps one-way commission and a 30 bps transaction tax on sales. Since we use realized transaction prices, we capture any price impact from trade. Based on our discussion of trading costs with TSE officials, our assumption regarding one-way commissions of 5 bps is likely lower than what many traders pay. Our qualitative results are similar if we run our analysis using the commission maximum of 14.25 bps. (See Appendix A for details regarding our return calculations.)

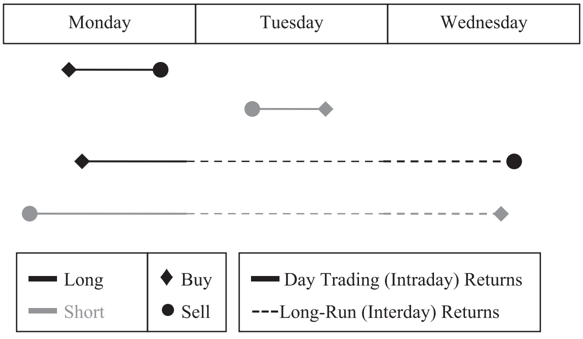

Fig. 2. Example of trading activity for a day trader.

It is important to include both round-trip and one-sided trades to measure the performance of day trading. Focusing only on round-trip trades would yield a biased measure of performance if investors sell winners and hold losers (i.e., exhibit the disposition effect). For example, assume some day traders randomly buy and sell (random traders), while others close only winning investments while riding losers (disposition traders). Were we to analyze only the profits of round-trip trades, it is clear that the disposition traders would have better round-trip returns than the random traders merely because they have a rule regarding when to close a position. Since the disposition effect is prevalent among Taiwanese investors and among day traders elsewhere,[10] it is important to include both round-trip and other trades when analyzing performance.

To test the robustness of our results, we also analyze the performance of trades that result in open positions. We begin by using trade data to build end-of-day positions for each investor.[11] If an investor buys a stock that creates a new end-of-day position in that stock (or increases an existing position), we track the performance of the position from the close of the trade date to five days following the trade date. If the stock is sold within the five-day window, we calculate the return on the position on the sale date using the sales price net of any transaction costs. We calculate the returns on short position similarly. Our main results use a five-day window, but the general tenor of the results is similar if we consider a one- or 10-day window.

In Fig. 2, we present an example of four trades by a day trader. The gray lines represent short positions, while the black lines represent long positions. The solid lines correspond to our intraday returns, while the dashed lines correspond to the returns earned on open positions in the five-day window following a trade.

To evaluate the performance of day traders, we estimate alphas relative to a market index. To calculate the alphas of intraday returns, we regress the day trading return on the market excess return (market return less risk-free rate) and report the intercept (alpha) from these regressions.[12] To calculate the alpha of the returns earned on open positions during the five-day post-trade window, we regress the position excess return (position return less risk-free rate) on the market

[10] Linnainmaa (2005) and Barber et al. (2007) document, respectively, that Finnish day traders and individual Taiwanese investors exhibit the disposition effect.

[11] Some errors inevitably occur in building positions since we do not know positions at the beginning of the dataset (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.

[12] Because day traders are not charged margin interest on intraday trades, we do not subtract the risk-free rate from the day trading return. Our results are unaffected by doing so as the risk-free rate during our sample period is 2.4 bps per day, which is small relative to the estimated alphas for intraday returns.

excess return. 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 risk-free rate is the one-year time deposit interest rate offered by the First Commercial Bank of Taiwan. The intercepts from these regressions are our measure of abnormal returns.

4. Results

In our main results, we sort day traders into groups based on a characteristic in year y and analyze the aggregate performance of each group in year $y+1$. We first consider sorts based on past day trading activity and then sort on past performance.

4.1. Active day traders

In Table 1, we present the gross and net performance of day traders sorted on prior day trading activity. We analyze the day trades and other trades of these investors in the months in which they day trade. 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 down to those with no prior day trading experience. We analyze the performance of each group in the year subsequent to ranking.

Consider the top 500 day traders (first row of Table 1). In aggregate, they earn positive gross returns on their day trading of 14.4 bps per day (t=21.08), but these profits do not survive costs because these active day traders lose 7.4 bps per day net of fees (t=−10.85). The returns to open

Table 1
Performance for sorts based on prior year day trading activity: 1993–2006.

Day traders are grouped based on prior year trading activity (e.g., “1–500” are the most active 500 day traders from year y). The table presents the aggregate performance for each group in the year following ranking (y+1). The day trading alphas are estimated using the following regression of daily returns: $R_{pt}=\alpha_p+\beta_p(R_{mt}-R_{ft})+\varepsilon_{pt}$, where R_{pt}, R_{mt}, and R_{ft} are the portfolio return, market return, and risk-free return, respectively. For intraday returns, we do not subtract the risk-free rate since interest is not charged for intraday trading. For position returns, the dependent variable is $R_{pt}-R_{ft}$. 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 5 bps one-way commission and a 30 bps transaction tax on sales. The returns to open positions are calculated on outstanding positions on the day of trade and are tracked through day t+5 (either marked to market or closed by an offsetting trade).

	Returns to day trading (t=0)						Returns to open positions (t=+1,+5)			
	Gross		Net							
	α (%)	t-stat	α (%)	t-stat	Beta	R-Sq	α (%)	t-stat	Beta	R-Sq
1–500	0.144	21.08	−0.074	−10.85	0.17	27%	0.050	4.21	0.91	79%
501–1,000	0.070	10.30	−0.136	−19.84	0.18	31%	0.019	1.89	0.90	83%
1,001–2,000	0.026	3.69	−0.168	−23.35	0.20	33%	0.004	0.39	0.89	83%
2,001–5,000	−0.020	−2.73	−0.205	−28.51	0.22	37%	−0.012	−1.30	0.90	86%
5,001–10,000	−0.061	−8.32	−0.237	−32.15	0.24	40%	−0.030	−3.51	0.90	87%
10,001–20,000	−0.093	−12.46	−0.258	−34.40	0.25	41%	−0.039	−4.78	0.91	88%
20,001–50,000	−0.121	−15.64	−0.269	−34.76	0.27	43%	−0.052	−6.70	0.92	90%
> 50,000	−0.146	−18.09	−0.264	−32.76	0.29	44%	−0.064	−8.69	0.96	91%
No prior yr rank	−0.140	−16.28	−0.243	−28.35	0.29	42%	−0.047	−6.12	1.00	91%

Table 2
Performance for sorts based on past day trading profits: 1993–2006.
Day traders are grouped based on prior year daily Sharpe ratio for day trading only (e.g., “1–500” are the 500 day traders from year y with highest daily Sharpe ratio). See Table 1 for a description of return calculations.

	Returns to day trading (t=0)						Returns to open positions (t=+1,+5)			
	Gross		Net							
	α (%)	t-stat	α (%)	t-stat	Beta	R-Sq	α (%)	t-stat	Beta	R-Sq
1–500	0.613	96.20	0.379	61.04	0.19	36%	−0.001	−0.14	0.83	86%
501–1,000	0.407	56.66	0.205	29.31	0.19	31%	0.005	0.53	0.84	84%
1,001–2,000	0.331	47.26	0.138	20.11	0.17	28%	0.003	0.30	0.85	86%
2,001–4,000	0.255	35.87	0.076	10.83	0.19	32%	0.006	0.70	0.88	88%
4,001–6,000	0.197	28.24	0.022	3.27	0.20	33%	−0.013	−1.63	0.88	88%
6,001–8,000	0.160	22.43	−0.009	−1.24	0.20	33%	−0.014	−1.70	0.87	88%
8,001–10,000	0.139	18.65	−0.026	−3.54	0.20	32%	−0.016	−1.92	0.89	87%
> 10,000	−0.115	−15.83	−0.289	−39.67	0.25	43%	−0.059	−7.39	0.92	89%
No prior yr rank	−0.142	−16.81	−0.250	−29.52	0.29	42%	−0.048	−6.25	0.98	91%

positions in the five-day post-trade window are reliably positive, but not sufficiently large to offset the negative returns earned on intraday trading. In combination, these results suggest that the most active day traders incur losses. The net returns assume a heavy commission discount, so the net losses from day trading grow when we assume commissions of 14.25 bps. For example, the net alpha earned by the 500 most active day traders is −7.4 bps assuming a 5 bps commission and −20.9 bps assuming a 14.25 bps commission. In untabulated results, we estimate that almost 10% of all day trading can be traced to these 500 very active day traders and approximately half of all of their trades are round-trip day trades.

It is clear from Table 1 that active day traders, despite failing to make money net of costs, earn higher returns than occasional day traders. The alphas on intraday returns is nearly monotonically decreasing as one moves from the most active day traders (top row of Table 1) to the least active day traders (bottom row of Table 1). In their analysis of the performance of individual and institutional investors in Taiwan from 1995 to 1999, Barber, Lee, Liu, and Odean (2009) document that, in aggregate, the trades of all individual investors lose money *before* transaction costs and that these losses grow at longer horizons. Thus, before transaction costs, 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 14.4 bps, is impressive.

4.2. *Performance persistence*

In Table 2, 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 net of transaction costs (i.e., the mean net day trading return divided by the standard deviation of day trading returns). We require a minimum of 10 days of day trading within the ranking year to rank an investor. Most of the gains (and losses) from trade tend to occur immediately following a trade (Coval et al., 2005; Barber et al., 2009; Grinblatt et al., 2012). So, by focusing on frequent traders and the returns earned on the day of trade, we likely obtain a more precise measure of investor skill.

We create eight groups based on prior day trading profitability—starting with the top 500 day traders and going down to those ranked below 10,000. We include a ninth group of unranked traders who day traded on at least one day but fewer than 10 days in the ranking year. During the ranking period, the top 500 traders have a mean Sharpe ratio of 0.66. Each of the top six groups (through 8,000 traders) has a mean Sharpe ratio greater than zero in each ranking year.

There is clear performance persistence. The top-ranked profit group (1–500) earns impressive alphas from day trading. The top five groups (or 6,000 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—both before and after fees.

For the top four profit groups (through 4,000 traders), the returns on open positions are not reliably different from zero and do not affect our conclusions regarding the profitability of these four groups. These results are qualitatively similar when we analyze the returns to open position for one or 10 days following the trade date. For the fifth profit group (4,001–6,000 traders), the returns on open positions are −1.3 bps per day and marginally significant ($t=-1.63$). When these returns are combined with the modest intraday profits (2.2 bps per day, $t=3.27$), we cannot conclude that this group earns reliably positive returns net of fees. Thus, the number of day traders who predictably profit from their day trading, assuming a 5 bps commission, is about 4,000 individuals. In untabulated analyses, we test the robustness of the conclusion that some day traders earn positive returns net of transaction costs by varying our assumptions regarding commissions paid by day traders. Assuming a 14.25 bps commission (the statutory maximum), the top three groups earn net alphas of 24.1 bps ($t=39.0$), 7.6 bps ($t=10.9$), and 1.1 bps ($t=1.6$). Thus, the number of predictably profitable day traders ranges from a low of 1,000 to a high of 4,000.

In the average year, about 450,000 individuals engage in day trading. While approximately 20% earn profits net of fees in the typical year, the results of our analysis suggest that less than 1% of day traders (4,000 out of 450,000) are able to outperform *consistently*. It is worth emphasizing the outsized alphas earned by the top 500 day traders. They pick up 61.3 bps on their day trading portfolio before costs and 37.9 bps after costs *per day*.

4.3. The probability of success

If outcomes are governed by luck, rather than skill, we expect success in one year to be independent of the probability of success in the next year. The preceding analysis suggests that the most successful investors indeed continue to earn strong returns. A related question is the following: Is the probability of being a winner in consecutive years greater than what we would expect by chance?

To answer this question, we define a day trader as a winner (loser) if the net profits on a trader's day trading portfolio are positive (zero or negative) in year y. We then construct a 2×2 contingency table and test the null hypothesis that winner-loser categorization in year y is independent of winner-loser categorization in year $y+1$ (i.e., outcomes are governed by luck). The results of this analysis are presented in Table 3. In Panel A, we present results for all traders who day trade in year y and $y+1$, while in Panel B we present results for traders with a minimum of $NT 600,000 in years y and $y+1$. In both samples, we comfortably reject the null hypothesis that winner-loser categorization is independent across years ($p<0.01$). For example, in Panel A,

Table 3
Tests of day trader winner-loser independence across years.

A day trader is defined as a winner (loser) if the net profits on a trader's day trading portfolio are positive (zero or negative) in year *y*. The table presents a 2×2 contingency table of being classified as a winner in year *y* and *y*+1. Panel A considers all traders with positive day trading in years *y* and *y*+1. Panel B considers all traders with day trading greater than $NT600,000 in years *y* and *y*+1.

		Year *y*+1		
		Winner	Loser	Row total
Panel A: Day trading in *y* and *y*+1				
Year *y*	Winner	6.6	13.3	20.0
	Loser	12.9	67.1	80.0
	Column Total	19.6	80.5	
	No. of Traders	3,813,485		
Panel B: Day trading > $NT 600,000 in *y* and *y*+1				
Year *y*	Winner	6.2	11.6	17.8
	Loser	11.0	71.2	82.2
	Column total	17.2	82.8	
	No. of traders	2,342,287		

we expect 3.9% (20.0% × 19.6%) of traders to be repeat winners by chance, but we observe 6.6% of traders are repeat winners. In Panel B, we expect 3.1% (17.8% × 17.2%)[13] to be repeat winners by chance, but we observe 6.2% are repeat winners. These results reinforce our prior conclusion that some day traders are skilled.

5. Sources of profits

How are successful day traders able to earn such strong returns before fees? Obviously, day traders are able to profit from short-term price movements. What is unclear is how they are able to forecast these movements. On the one 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. On the other 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. In this section, we consider both possibilities.

[13]The probability of earning positive abnormal returns net of transaction costs decreases when we require a minimum trade level of $NT 600,000 in consecutive years. This is to be expected if the mean net abnormal return for a trader is negative, which is the case for the vast majority of day traders. As a day trader engages in more trading, his average performance will be more precisely estimated and the probability of observing a positive mean abnormal return for all but the select group of skilled day traders will decrease.

Table 4
Day trading performance around earnings announcements for day traders sorted on past day trading profits: 1993–2006.

The table presents mean daily abnormal returns (α) to day trading only for stocks that are trading in an event window from $t=-3,+1$ relative to an earnings announcement day ($t=0$). Day traders are grouped based on prior year daily Sharpe ratio based on day trading returns (e.g., "1–500" are the top 500 day traders from year y). See Table 1 for a description of return calculations.

	α (%)	*t*-stat	α (%)	*t*-stat	α (%)	*t*-stat
	Earnings announcement window		Non-announcement window		Announcement–non-announcement	
1–500	0.655	46.79	0.589	31.66	0.066	2.83
501–1,000	0.465	32.81	0.376	20.04	0.089	3.78
1,001–2,000	0.378	30.51	0.306	18.10	0.072	3.45
2,001–4,000	0.289	23.92	0.226	13.26	0.063	3.01
4,001–6,000	0.239	19.37	0.166	9.65	0.073	3.44
6,001–8,000	0.191	14.80	0.128	7.08	0.062	2.80
8,001–10,000	0.176	13.92	0.109	6.16	0.067	3.07
>10,000	−0.104	−8.92	−0.122	−7.05	0.018	0.85
No prior yr rank	−0.138	−11.66	−0.138	−7.83	0.000	0.00

To preview the results of this section, we find some evidence that day traders possess private information or react quickly to public information. Specifically, profitable day traders earn particularly strong returns in small, volatile stocks and around earnings announcement. In contrast, we find weak evidence that liquidity provision is the main source of day trading profits. Profitable day traders tend to place aggressive orders, and day traders who follow passive order strategies fail to earn positive returns net of transaction costs.

5.1. Are day traders informed?

5.1.1. Earnings announcements

Are the strong returns of profitable day traders a result of better information about a firm's fundamentals? This is a difficult question to address definitively, but we attempt to provide some insight on this issue by analyzing the returns to day trading around earnings announcements. Earnings announcements are economically important and closely watched; as a result, earnings announcements are a logical place to look to determine if day traders are capitalizing on superior (or perhaps inside) information.

Using the TSE databank, we identify all earnings announcements for TSE stocks. We then identify trades that occur within a five-day window that begins three days prior to the announcement and ends the day after the announcement. We separately analyze the returns of day traders sorted on the basis of their past profitability as in Table 2; however, we now separately analyze the returns of stocks that are within the five-day announcement window and stocks that are outside the announcement window (non-announcement stocks). If day traders have superior information, we expect the returns on day trading during earnings announcements to be higher than returns during other periods since information asymmetry is arguably greater during announcement periods.

The results of this analysis are presented in Table 4. The first two columns present the alphas for stocks traded during the five-day earnings announcement window, while the next two columns present the alphas during non-announcement periods, and the last two columns present the difference in alphas between the announcement and non-announcement periods. The gross alphas for the most profitable traders around earnings announcements are higher than those earned during non-announcement periods. For example, the top profit group earns 65.5 bps on trades made during announcement periods and 58.9 bps on trades during non-announcement periods; the spread of 6.6 bps is reliably positive. We observe similar results for traders ranked among the top 10,000 based on prior year performance. However, less profitable day traders and those with insufficient activity to be ranked (the last two rows of Table 3) incur losses of equal magnitude during announcement and non-announcement periods. These results are generally consistent with the hypothesis that the best day traders earn strong returns during periods of high information asymmetry.

5.1.2. Hard-to-value stocks

If successful day traders profit from identifying temporary mispricings (perhaps prior to or quickly following information that would correct the mispricing), we would expect the profits of successful day traders to be concentrated in hard-to-value stocks, where mispricings are more likely to occur and are more likely to be large. To test this conjecture, in the spirit of Baker and Wurgler (2006), we sort stocks by size (small, medium, and big) and volatility (low, medium, and high). In June of year y, we rank stocks based on size or volatility. Firm size is measured as market cap (price times shares outstanding). Stocks ranked in the bottom third of market cap are small stocks, those in the top third are big stocks, and the rest are medium size stocks. Volatility is measured using the standard deviation of daily returns from July of year $y-1$ to June of year y, where we require a minimum of 50 daily return observations. Stocks ranked in the bottom third of daily return standard deviation are low volatility stocks, those in the top third are high volatility stocks, and the rest are medium volatility stocks.

We estimate the returns to day trading for each of the profit groups of Table 2 for small/medium/big stocks and low/medium/high volatility stocks. For parsimony, we present results only for gross intraday returns; the patterns for net intraday returns are similar. We conjecture that successful day traders will earn strong returns in small or volatile stocks.

The results of this analysis are presented in Table 5. In Panel A, we present results for sorts based on firm size. For each profitability group, day traders earn stronger returns in small stocks than they do in big stocks. The difference (small-big) is particularly pronounced for the most successful day traders. These patterns are generally consistent with the notion that successful day traders earn strong returns in small stocks, which are hard to value.

In Panel B of Table 5, we present results for sorts based on stock volatility. With the exception of relatively inexperienced day traders, each profitability group earns stronger returns in high-volatility stocks. The difference in returns earned between high versus low-volatility stocks is not as pronounced as the difference in returns earned on small versus big stocks. Nonetheless, the general tenor of the results is similar. With the exception of the very top performance group, which earns strong returns in both high- and low-volatility stocks, successful day traders appear to earn stronger returns in high-volatility stocks.

5.2. Are day traders suppliers or demanders of liquidity?

A natural place to look for profitable day trading is in the provision of liquidity. Perhaps day traders provide liquidity to uninformed traders by placing passive limit orders. As groundwork for this analysis, we calculate the closing effective percentage spread for stocks trading on the TSE. This analysis gives us a sense for the size of the spread and potential profits from liquidity provision in Taiwan. Each year, we use daily closing prices (P) and the midpoint of the last

Table 5
Day trading profits in hard to value stocks, 1993–2006.

The table presents mean daily abnormal returns (α) from day trading in small/medium/big stocks (Panel A) and high/medium/low volatility stocks (Panel B). See text for details of firm size and volatility cutoffs. Day traders are grouped based on prior year daily Sharpe ratio for day trading only (e.g., "1–500" are the 500 day traders from year y with highest daily Sharpe ratio). See Table 1 for a description of return calculations.

	α (%)	t-stat	α (%)	t-stat	α (%)	t-stat	α (%)	t-stat
	Panel A: Profits in small vs. big stocks							
	Small stocks		Medium stocks		Big stocks		Small-Big	
1–500	0.828	55.28	0.636	65.48	0.586	82.75	0.242	15.59
501–1,000	0.603	40.89	0.455	45.22	0.378	46.66	0.226	14.91
1,001–2,000	0.517	37.68	0.373	39.83	0.305	40.02	0.212	15.63
2,001–4,000	0.402	33.93	0.286	31.64	0.237	30.45	0.164	14.14
4,001–6,000	0.328	28.11	0.214	24.94	0.184	24.06	0.145	12.46
6,001–8,000	0.270	22.02	0.177	20.06	0.147	18.77	0.123	10.13
8,001–10,000	0.244	18.32	0.147	15.62	0.126	15.54	0.118	8.94
$>$10,000	−0.102	−10.99	−0.146	−17.63	−0.112	−14.47	0.011	1.32
No prior yr rank	−0.114	−10.85	−0.167	−17.65	−0.140	−15.61	0.025	2.77
	Panel B: Profits in high vs. low volatility stocks							
	High volatility		Medium volatility		Low volatility		Hi-Low	
1–500	0.633	68.37	0.567	72.89	0.621	82.16	0.012	1.15
501–1,000	0.462	45.61	0.371	43.81	0.334	42.63	0.128	11.58
1,001–2,000	0.382	41.40	0.298	38.31	0.253	34.33	0.129	13.59
2,001–4,000	0.300	32.87	0.223	29.00	0.185	26.58	0.115	13.23
4,001–6,000	0.240	27.49	0.163	21.14	0.134	18.68	0.106	12.48
6,001–8,000	0.200	22.38	0.123	15.92	0.105	14.08	0.095	10.93
8,001–10,000	0.178	18.97	0.104	13.01	0.072	9.58	0.106	11.65
$>$10,000	−0.111	−12.67	−0.135	−18.13	−0.126	−18.70	0.015	2.07
No prior yr rank	−0.147	−13.88	−0.162	−18.95	−0.114	−15.66	−0.033	−3.86

unfilled buy and sell orders (M) and calculate the effective percentage spread for each stock-day combination as $2|P-M|/M$. We then calculate the average spread across stocks on a particular day and then average across days within a year to generate an annual estimate of the percentage effective spread for 1992–2006. Across the 15 years, the average percentage effective spread for stocks trading on the TSE is 64 bps, with no particularly strong time trend in the average spread; it ranges from a low of 52 bps in 1996 to a high of 78 bps in 2002. The size of these spreads makes it plausible that, even with a 30 bps transaction tax, liquidity provision by day traders could be a profitable trading strategy.

To determine whether day traders are earning gross profits by providing liquidity, 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

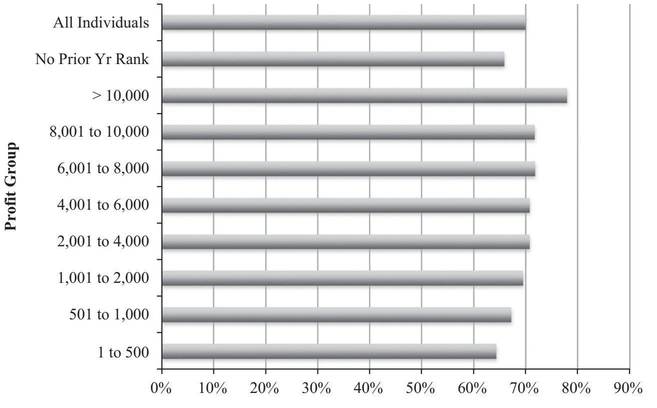

Fig. 3. Order aggressiveness for profit groups. Profit groups are formed in year *y*; aggressiveness of trades is analyzed in year *y*+1. The figure presents the mean daily percentage of trades that emanate from aggressive orders for each profit group.

all orders as aggressive or passive by comparing order prices to the most recent unfilled limit order prices at the time of the order. Orders to buy with prices at or in excess of the most recent unfilled sell limit order we categorize as aggressive; those with prices at, or below, the most recent unfilled buy limit order we categorize as passive; those with an order price between the two unfilled limit order prices we categorize as indeterminate. Our algorithm for sells is analogous. 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% of all trades as passive or aggressive.[14]

Overall, about 70% of 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, although corporations tend to be less aggressive than foreigners and dealers. Even if investors placed similar numbers of aggressive and passive limit orders, we would expect a higher percentage of trades to originate from aggressive limit orders, since aggressive limit orders are more likely to be executed.

In Fig. 3, we present the proportion of trades that emanate from aggressive limit orders for trader groups formed on the basis of past profitability, where profit groups are formed as described in Table 2. We rank traders based on profitability in year *y* and analyze the aggressiveness of their trades in year *y*+1. We sum the total value of aggressive and passive trades for each profit group and then calculate the proportion of aggressive trades on each day. The figure presents the mean proportion across all days for a particular profit group.

In general, day traders place orders that are in the same ballpark as the aggressiveness we observe for the average individuals. Among day traders, the proportion of trades that originate from aggressive orders ranges from 64% to 78%, while the proportion for all individual investors is 70%. The 500 most profitable day traders are somewhat less aggressive than other day traders (64% of their trades emanate from aggressive orders). While there is some variation in order

[14]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 are the source of the problem. Though annoying, this type of data error should not introduce any bias into our results.

Table 6
Performance for sorts based on prior year order type: 1993–2006.

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 mean abnormal return (α) based on the aggregate performance for each group in the year following ranking (y+1). See Table 1 for a description of return calculations.

	Returns to day trading					
	Gross		Net			
	α (%)	t-stat	α (%)	t-stat	Beta	R-Sq
Passive (1a)	0.038	4.07	−0.193	−20.64	0.26	31%
1b	−0.001	−0.06	−0.248	−26.12	0.28	34%
2	−0.064	−7.26	−0.312	−35.48	0.27	36%
3	−0.106	−11.97	−0.354	−40.28	0.26	35%
4	−0.104	−11.74	−0.354	−40.10	0.26	35%
5	−0.097	−11.34	−0.360	−42.16	0.27	38%
6	−0.078	−9.21	−0.360	−42.67	0.24	34%
7	−0.060	−6.97	−0.341	−39.74	0.24	33%
8	−0.095	−11.15	−0.381	−44.50	0.25	36%
9	−0.111	−12.08	−0.396	−43.07	0.27	35%
10b	−0.087	−9.33	−0.396	−42.25	0.26	33%
Aggressive(10a)	−0.124	−13.03	−0.419	−44.39	0.27	34%
No prior yr rank	−0.104	−13.46	−0.355	−45.91	0.27	43%

aggressiveness, suggesting the most profitable day traders make greater use of passive orders, the variation is economically modest and is unlikely to explain the strong returns of the most profitable day traders as the majority of their trades emanate from aggressive orders.

We further explore this issue by ranking day traders by the aggressiveness of their orders in year y and analyzing their performance in year y+1. We create 10 “aggressiveness” deciles ranging from one (most passive) to 10 (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 that we can classify as passive or aggressive to be included in the rankings, so the traders we analyze are fairly active relative to the population of individual investors. The most passive group (1a) has only 16% aggressive trades in the ranking year (and 20% in the following year), while the most aggressive group (10a) has 97% aggressive trades in the ranking year (and 94% in the following year).

In Table 6, we present the profitability of day trading based on the aggressiveness partitions. While passive day traders earn profits before costs, the returns are modest (3.8 bps per day) and fail to survive transaction costs. All partitions lose money after costs. The losses tend to be higher for the most aggressive partitions. Thus, the use of passive orders does seem to predict cross-sectional variation in day trader performance (a result we confirm in a multivariate analysis in the next section). However, day traders who focus on passive strategies fail to earn positive net alphas.

In summary, providing liquidity does not appear to be the major source of day trading profits. Day traders, even the most profitable day traders, place orders that are usually aggressive. Furthermore, day traders who rely most heavily on passive orders do not, on average, earn positive gross trading profits. While the savvy use of passive orders likely boosts the profits earned by some day traders, it does not completely explain the outsized returns that they earn.

5.3. Forecasting profitability

Our analysis indicates that 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. We would like to better understand the characteristics of profitable day traders.

We estimate a logistic regression in which the dependent variable is a dummy variable that takes on a value of one if the net profits on a trader's day trading portfolio are positive in year *y*. We choose to use the dummy variable as a dependent variable in lieu of a trader's return or Sharpe ratio for two reasons. First, the estimation strategy allows us to say something about the probability of earning a positive net return. Indeed, we find it takes a truly remarkable profile to garner an even 50-50 chance of being profitable. Second, we are interested in identifying the characteristics of profitable day traders rather than (for example) characteristics that predict variation in the losses of day traders. The logistic regression is well suited to this task. Nonetheless, our results are qualitatively similar when we use the Sharpe ratio of returns as the dependent variable in our analyses.

To reduce the impact of occasional day trading, which may be motivated by the social or entertainment values of trading, we require that an investor engage in a minimum of $NT 600,000 in day trading during the year. (We explore the use of higher and lower cutoff values and find generally similar results to those reported here.) We include a range of independent variables designed to capture the experience, sophistication, and skill of day traders. All independent variables are measured cumulatively through year $y-1$, while the dummy variable for profits is based on profitability net of fees on an investor's day trading portfolio in year *y*.

We include two measures of past success (profits): *Sharpe Profit* and *Sharpe Return*. These Sharpe ratio measures are calculated as the mean net daily return (or dollar profit) from day trading divided by the daily standard deviation, where we require a minimum of 10 days of day trading to be included in the analysis. We include dollar profits to capture investors who might consistently earn low returns on a large dollar value of trades.

We also test for any gains from specialization on two dimensions. We include the concentration of an investor's trades in the five most traded stocks (*Percent Top Five Stocks*). This variable is designed to capture any gains from specializing in the trading of a small group of stocks. To capture whether there are gains to specializing in day trading, we measure the percentage of an investor's trades that are round-trip day trades (*Percent Day Trades*).

Short selling is a reasonable proxy for investor sophistication. Thus, we include the proportion of a day trader's round-trip day trades that were short sales, including buys to cover a short position (*Percent Short*). The percentage of trades that emanate from aggressive orders measures whether a day trader is a liquidity demander or provider (*Percent Agg. Trades*). Finally, we include two measures of experience: *Log Experience* is the log of the number of days since the trader began day trading as of the beginning of year *y*, while *Log Volume* is the log of the dollar volume of prior trading.

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 7, we present the annual coefficient estimates, the mean coefficient estimate across the year, and the standard error of the mean.

In the first two rows of Table 7, 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 the

Table 7
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 *y*. The probability of a positive profit is estimated using a logistic regression in which the dependent variable is the profit dummy. Independent variables for each investor include the Sharpe ratio of past day trading profits (*Sharpe Profit*) and day trading returns (*Sharpe Return*), the percentage of trading concentrated in the top five stocks (*Percent Top Five Stocks*), the percentage of trades that were short sales (*Percent Short*), the percentage of trading devoted to day trading (*Percent Day Trade*), the percentage of aggressive trades (Percent Agg. Trades), the log of the number of days since a trader's first day trade as of the beginning of year *y* (*Log Experience*), and the log of the dollar volume of prior trading (*Log Volume*). 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 based on the change in the probability of being profitable when the independent variable under consideration is changed from the 25th to 75th percentile of the distribution of the independent variable while remaining variables are set to their mean values.

	Intercept	**Sharpe profit**	**Sharpe return**	**Percent top five stocks**	**Percent short**	**Percent day trades**	**Percent agg. trades**	**Log exper.**	**Log volume**
Variable mean	0.814	−0.106	−0.110	0.167	0.071	0.194	0.713	5.525	1.222
Probability impact		2.8%	7.3%	1.2%	0.2%	−0.1%	−0.5%	0.3%	0.4%
	Coefficient estimates								
Coef. mean	−1.13	1.11	2.55	0.53	0.21	−0.04	−0.25	0.01	0.02
Std. error	0.05	0.10	0.20	0.05	0.04	0.07	0.05	0.01	0.01
1994	−1.28	0.80	1.23	0.37	0.11	−0.06	−0.06	−0.05	0.06
1995	−1.19	1.61	1.68	0.65	0.28	−0.36	−0.04	−0.03	0.03
1996	−1.17	1.69	1.87	0.94	0.19	−0.20	−0.11	−0.03	0.05
1997	−1.61	1.30	1.92	0.56	0.32	−0.15	0.06	0.01	0.08
1998	−1.31	1.15	2.10	0.40	0.12	−0.36	−0.23	0.03	0.06
1999	−1.18	0.99	2.49	0.36	0.09	−0.31	−0.01	0.04	0.04
2000	−0.88	0.48	3.09	0.27	0.26	−0.08	−0.26	0.04	0.00
2001	−0.96	0.81	2.79	0.37	−0.05	−0.08	−0.33	0.04	0.00
2002	−1.06	0.74	3.37	0.56	0.48	0.07	−0.50	0.01	0.00
2003	−1.05	1.03	3.38	0.69	0.29	0.32	−0.55	0.00	−0.01
2004	−0.95	1.27	3.05	0.66	0.22	0.06	−0.41	0.02	0.00
2005	−1.10	1.70	2.73	0.67	0.16	0.20	−0.39	0.00	−0.04
2006	−0.96	0.84	3.51	0.36	0.32	0.46	−0.38	0.01	−0.06

change in the probability of being profitable that results when one moves from 25th to 75th percentile of the distribution of the independent variable under consideration while all remaining variables are set to their mean.

As we discuss these results, it's useful to note the baseline probabilities of earning an intraday profit for the set of day traders with observations on all independent variables in our logistic regression is 18.6% (i.e., 81.4% of day traders in this sample lose money unconditionally). Consistent with our univariate results, profitability measures are strong predictors of trading success. Both Sharpe ratio measures on returns and profits predict future success. Moving from the 25th to the 75th percentile on the profit variable improves the chances of being profitable by 2.8 percentage points for profits and 7.3 percentage points for returns. By a large margin, these profitability measures are the best predictors of the probability of future profitability.

Measures of sophistication and specialization predict success. Day traders who short and those who concentrate in a few stocks are more likely to be successful. These effects, although statistically significant, are economically modest. Consistent with our prior results, we find that order aggressiveness is able to reliably forecast profitability; the negative relation between order aggressiveness and the probability of success suggests that day traders who employ a larger fraction of passive orders perform better. However, the predictive power is quite small relative to the importance of past profits or returns.

Experienced and heavy day traders are more likely to be successful. Consistent with our prior results, the log of volume is a reliable predictor of success; heavy day traders perform better than occasional day traders. Experience is a less reliable predictor of success. Both volume and experience are economically weak predictors relative to past profits.

Overall, the results indicate that heavy traders with past success and experience, who are willing to short sell, employ passive trading strategies, and concentrate in a few stocks that have the greatest probability of turning a profit. However, only day traders with extremely rare characteristics would have even odds of turning a profit net of fees. For example, relative to a baseline probability of being profitable, consider a day trader who is at the 75th (25th) percentile for independent variables that positively (negatively) predict profitability. Such a trader would improve his chances of profitability from the baseline of 18.6% to 31.4%. Thus, only day traders with truly remarkable characteristics can reasonably expect to earn profits net of fees.

6. Discussion

Although the vast majority of day traders in Taiwan lose money, 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 (see Tables 1 and 2) and individual investors in general (see Barber et al., 2009). 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 day traders who employ passive limit orders are somewhat more profitable than others, the economic significance of order aggressiveness in predicting profitability is economically weak. Moreover, day traders who focus on passive limit order strategies fail to earn returns net of fees and more than 64% of the trades executed by the most successful day traders emanate from aggressive limit orders. Aggressive limit orders will lead to day trading profits when traders are able to anticipate short-term price changes.

Successful day traders in Taiwan appear to profit predominantly from forecasting short-term price movements in periods when information asymmetry is high (e.g., around earnings announcement) or in hard-to-value stocks (e.g., small or volatile stocks). This evidence suggests that day traders either possess private information or react more quickly to public information signals in their trading strategies. Harris and Schultz (1998) document that SOES bandits are able to profit from trading with market makers who ostensibly are better informed and better financed. Harris and Schultz 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 Murphy (2005a) 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 15 day traders studied by Garvey and Murphy profit from vigilance and quick reactions.

It is also possible that day traders in Taiwan possess private (inside) information. Insider trading laws in Taiwan are similar to those in the U.S. For example, directors and officers of a firm cannot trade on the basis of material private information; anyone acquiring private information also is precluded from trading. Penalties include fines and prison time. During our sample period, 35 cases were prosecuted (about two to three per year) and about half (17) resulted in a guilty verdict (11 resulted in prison time). While we cannot completely rule out the possibility that insider trading drives the profitability of successful day traders, the consistent profitability of successful day traders in periods outside of earnings announcement windows and in large and less volatile stocks suggests that insider trading is not the entire story.

7. Conclusion

Day trading is an equilibrium feature of trading on the Taiwan Stock Exchange—accounting for almost 17% of total trading volume during our sample period. Individual investors account for virtually all day trading (over 99% of day traders and 95% of day trading volume). In an average year, 450,000 individual investors day trade. Of these, 277,000 engage in day trades that exceed $NT 600,000 ($US 20,000), but only about 20% of this population is able to profit after a reasonable accounting for trading costs.

Most successful day traders in Taiwan are merely lucky, but a small group of day traders are skilled, earning predictably high returns. We document strongly persistent cross-sectional variation in day trading skill. The 500 most successful day traders from year y go on to outperform the least successful day traders by over 60 bps per day in year $y+1$. The top day traders earn gross returns of 37.9 bps per day—more than enough to cover commissions and a hefty transaction tax on sales of 30 bps. Our auxiliary analyses indicate that the most profitable day traders are *not* primarily liquidity providers, as they tend to place aggressive orders in anticipation of price moves. The most successful are heavy day traders with a history of profits who are willing to short and who concentrate in a few stocks.

Cross-sectional variation in investor ability is statistically and economically large. This observation runs counter to the classic efficient markets view (e.g., Fama, 1991) in which private information is rare and investors are protected by market prices that fully reflect all information.

In aggregate and on average, trading is hazardous to one's wealth. However, the performance penalty associated with trading is not borne equally by all and is not confined to trading costs.

Some traders are consistently dismal stock pickers; for a select few, trading proves to be a profitable endeavor.

Appendix A. Details of return calculations

We calculate the intraday return from day trading on day t for a particular group (g) of investors weighted by the value of investors' trades:

$$r_{gt} = \frac{\sum_i \sum_j (S^L_{ijt} - B^L_{ijt}) + (S^S_{ijt} - B^S_{ijt})}{\sum_i \sum_j (B^L_{ijt} + S^S_{ijt})} \tag{A1}$$

where B and S denote the value of buys and sells (with superscripts L and S for long and short transactions, respectively) on day t in stock i by investor j. For long positions, the sales price (S^L_{ijt}) is the actual transaction price or the closing price if the long position is not closed out prior to the end of trading. For short positions, the purchase price (B^S_{ijt}) is the actual transaction price or the closing price if the short position is not closed out prior to the end of trading.

Consider a concrete example where an investor buys a stock for \$100 and sells later in the day for \$102. On the same day, the investor shorts a stock (the same stock or a different stock) for \$100 and later covers the short with a purchase at \$97. The investor makes profits of \$5 = (102−100)+(100−97). We scale the dollar profits by the total value of the opening positions, \$200 = \$100+\$100. Thus, we assume the investor put \$200 of capital at risk and earned an intraday return of \$5/\$200 = 2.5%. This is an accurate representation of the returns if the investor trades in parallel (i.e., both positions are open at the same time). For investors who trade sequentially, we correctly calculate dollar profits of \$5, but the capital at risk would be \$100 rather than \$200 as the \$100 would be deployed sequentially. Thus, we always estimate the correct sign of returns, but for day traders who trade sequentially, our return estimates are biased toward zero. In addition, we do not know the extent to which traders use leverage, which would increase the magnitude of returns for both gains and losses, but again the sign of the gains and losses would be the same as those in our calculations. In summary, the sign of the day trading returns that we calculate is accurate, although the magnitudes may differ because of sequential trading or the use of leverage.

When we calculate net returns, we deduct a 5 bps commission for all trades (10 bps round-trip commission) and a 30 bps transaction tax for sales. Put differently, buys cost 5 bps (C_b) and sells cost 35 bps (C_s). We also increase the capital requirements to reflect the total cost of the opening positions:

$$r^{net}_{gt} = \frac{\sum_i \sum_j (S^L_{ijt} - B^L_{ijt}) + (S^S_{ijt} - B^S_{ijt}) - c^*_b (B^L_{ijt} + B^S_{ijt}) - c_s (S^L_{ijt} + S^S_{ijt})}{\sum_i \sum_j (B^L_{ijt} + S^S_{ijt}) + c_b B^L_{ijt} + c_s S^S_{ijt}}, \tag{A2}$$

Continuing our example from above, the net return for the trader would be:

$$\frac{(102-100) + (100-97) - 0.0005(100+97) - 0.0035(102+100)}{(100+100) + 0.0005 * 100 + 0.0035 * 100} = \frac{4.19}{200.40} = 2.09\%.$$

Note the net return (2.09%) is roughly 40 bps (the total round-trip trading costs of 10 bps in commissions and 30 bps in transaction tax) less than the gross return (2.50%). The shortfall is slightly greater than 40 bps because we also increase the capital required to open the positions.

There is an analogous calculation for the return on the remaining portfolio. Define V as the value of the end-of-day open position in a stock with superscripts for L and S for long and short positions, respectively. We calculate the return to the remaining portfolio (rp) as the daily profits to long and short positions scaled by the position value entering the day:

$$rp_{gt} = \frac{\sum_i \sum_j (V^L_{i,j,t} - V^L_{i,j,t-1}) - (V^S_{i,j,t} - V^S_{i,j,t-1})}{\sum_i \sum_j (V^L_{i,j,t-1} + V^S_{i,j,t-1})}, \tag{A3}$$

Stocks still held at the end of day t are marked to market at the end-of-day closing price for the stock. For long positions, stocks sold on day t are valued at the sales price less an assumed transaction cost of 35 bps. For short positions, stocks bought to cover shorts on day t are valued at the purchase price less an assumed transaction cost of 5 bps.

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