Do Day Traders Rationally Learn About Their Ability?

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Abstract

We analyze the performance of and learning by individual investors who engage in day trading in Taiwan from 1992 to 2006 and test the proposition that individual investors rationally speculate as day traders in order to learn whether they possess the superior trading ability. Consistent with models of both rational and biased learning, we document that unprofitable day traders are more likely to quit and that day traders begin with relatively small trades that increase as they gain experience. Inconsistent with models of rational speculation and learning, we document that the aggregate performance of day traders is negative and that over half of day trading can be traced to traders with considerable experience and a history of losses.

Recent papers (Mahani and Bernhardt (2007) and Linnainmaa (2010)) develop models in which an individual investor rationally chooses to trade speculatively—knowing that most other individuals lose money through speculation—in order to learn whether or not she has the ability to reliably profit through speculation. In these models, investors do not initially know their own abilities and rationally infer these by observing their trading performance. Gervais and Odean (2001) present a model in which biased learning leads successful investors to become overconfident. In this model, too, investors do not initially know their own abilities and must infer these from performance. However, when they are successful, these investors irrationally attribute success disproportionately to their ability rather than luck, leading investors to overestimate their own abilities and trade too aggressively; even investors with more past failures than successes may become overconfident by overweighting their successes.

We test the predictions of rational Bayesian learning models by analyzing the performance of day traders in Taiwan. We focus on day traders, those who buy and sell the same stock within a day, as these traders are almost surely speculators. Using the complete transaction data for the Taiwan Stock Market over 15 years (1992 to 2006), we find evidence of learning among day traders. The majority of day traders quit relatively quickly (80% of all day traders quit within two years), and poor performers are more likely to quit. These results are consistent with the models of both rational and biased learning. In this respect, our paper complements the emerging evidence that learning is an important factor in the behavior of individual investors. Using Finnish data, Seru, Shumway, and Stoffman (2010) document investors not only learn about their ability by trading, but also get better with experience. Linnainmaa (2010) calibrates a structural model in which investors rationally learn about their ability through trading using trading records of active individual Finnish investors. Consistent with the prediction of his model, investors are more likely to increase trade size after successful trades and more likely to decrease trade size or quit trading after unsuccessful trades. Furthermore, the size and quitting effects are stronger early in an investor's career, when his or her prior beliefs about ability are more diffuse. Using US broker data, Nicolosi, Peng, and Zhu (2009) show that trade intensity increases following signals of strong performance. Analyzing data from the National Stock Exchange in India, De et. al. (2010) document that investors increase trading in response to recent profits and that the sign of profits matters more than their magnitude.

Previous tests of rational learning models of trading have focused primarily on confirming evidence, e.g., do investors increase (decrease) trading in response to successful (unsuccessful) trades? To properly test these models it is, however, equally or more important to also look for disconfirming evidence. While we, too, find clear evidence of learning, we also document behavior that is not consistent with rational Bayesian learning as modeled by Mahani and Bernhard (2007) and Linnainmaa (2010) for two reasons:

First, if the entry (and exit) of new speculators who are testing their trading acumen is stable over time, then the sign of the expected lifetime profits of new speculators is the same as that of aggregate speculator profits. Therefore risk-averse or risk-neutral potential speculators with no special prior knowledge of their abilities should only "trade to learn" if aggregate speculator profits are positive. In fact, using complete data for the Taiwan market, the aggregate performance of day traders net of fees is negative in each of the 15 years that we study. A profit-maximizing risk-averse (or risk-neutral) Bayesian investor would not enter a market if her expected lifetime profits were negative.

Second, though performance affects day trader survival, many poor traders persist. In each year (y) from 1995 to 2006, we sort day traders into four groups based on their day trading through the prior year (y-1): occasional day traders, first-time day traders, unprofitable traders, and profitable traders. We define occasional day traders as those with less than 20 days of prior day trading experience, first-timers as those with no prior day trading experience, and unprofitable (or profitable) day traders as those with a minimum of 20 days of day trading experience and negative (positive) mean return to their prior day trading experience. Though our dataset begins in 1992, we begin this analysis in 1995 so as to build up a three-year history of day trading activity and performance. In the average year, occasional day traders and first-timers account for 74% of all day traders, but only 34% of total day trading volume. Day traders with prior profits account for only 1.6% of all day traders, but represent 12% of total day trading volume. Day traders with a history of losses represent 24% of all day traders, but account for over half of all day trading volume (54%).

The rest of this paper is organized as follows. After reviewing related research (section I), we discuss Taiwan market rules, data, and methods (section II). In section III, we present the performance of day traders sorted in aggregate and partitioned by past performance and trading activity. In section IV, we explore the source of profits for profitable day traders. In section V, we explicitly test the learning models. After discussing our results (section VI), we make some concluding remarks (section VII).

I. Learning by Speculators

The suggestion that investors learn from experience is neither novel nor controversial.[*] Learning is a ubiquitous feature of human experience. From a welfare and policy perspective, the question is not whether investors learn, but how well they learn. In this section we develop testable predications that emanate from a rational model of learning and highlight the predictions would discriminate between rational and biased models of learning.

Mahani and Bernhardt (2007) argue that rational Bayesian learning can explain several empirical regularities: cross-sectionally, most speculators lose money; large speculators outperform small speculators; past performance positively effects subsequent trade intensity; most new traders lose money and cease speculation; and performance shows persistence. Similar to Mahani and Bernhardt (2007), Linnainmaa (2010) develops a structural model of rational learning. Using trading data from Finland, he finds investors with poor performance are likely to quit and trading intensity increases following good performance.

In Mahani and Bernhardt (2007), novice speculators lose while the experienced profit, but aggregate performance should be positive and represent an upper bound on the return to day trading. To see the logic behind this assertion, consider the following simple, concrete, example. Suppose that 21 new speculators try trading each year. Only one of these has skill; 20 are unskilled. Unskilled speculators trade for one year, lose $1, and quit. Skilled speculators trade for 10 years, earn $1 each year and quit. Thus aggregate speculator profits each year are -$10. Because skilled speculators stay in the market longer, skilled speculators account for a greater fraction of active speculators (i.e., 10/30) than of new speculators (i.e., 1/21). Expected lifetime profits for a new speculator are $(1/21)\$10+(20/21)(-\$1)=-\$0.476$. Note that aggregate annual profits divided by the number of new speculators each year are equal to expected lifetime profits (i.e., -

[*] A number of papers document investor learning in various forms including Feng and Seasholes (2005), Seru, Shumway, and Stoffman (2007), Nicolosi, Peng, and Zhu (2009), Chiang, Hirshleifer, Qian, and Shreman (2010), Choi, Laibson, Madrian and Metrick (2010), De, Gondhi, and Pochiraju (2010), and Odean, Strahilesvitz, and Barber (2010).

$10/21 =-$ 0.476) and that aggregate annual profits divided by the number of all speculators trading in a year (e.g., -10/30 = -$ 0.333) are of the same sign but lower magnitude than expected lifetime profits. Thus, when aggregate profits are negative, they provide an upper limit to the unconditional expected lifetime profits of a speculator. If traders have rational prior beliefs about the unconditional expected lifetime profits from engaging in speculations, then the aggregate performance of speculators should be positive. This leads to our first null hypothesis:

H1: The aggregate performance of day traders is positive (non-negative).

The alternative is that the aggregate performance of day traders is negative. This is consistent with traders holding biased prior beliefs about the unconditional expected lifetime profits from trying day trading.

In the rational learning models, traders test the waters of speculation with small initial trades. Successful traders persist in trading and increase their trade sizes. Unsuccessful traders quit trading after the accumulation of negative signals outweighs their positive initial prior beliefs about their ability. Gervais and Odean (2001) develop a model in which investors take too much credit for their success and thus, relative to a Bayesian, overweight successes when learning about their ability. In their model, too, successful investors have more ability than unsuccessful ones and investors respond to good performance by trading more aggressively. In contrast to the rational Baysian model, their model can also explain persistent trading by previously unsuccessful traders; these traders put too much weight on successes and too little on failures when updating beliefs about their abilities

Persistent trading in the face of losses is not consistent with the models of rational learning. However, it is difficult to disentangle whether an unprofitable day trader is persisting because of biased learning or biased priors beliefs. Without a clear and accurate model of quickly traders should learn from losses coupled with estimates of prior beliefs, one cannot say precisely how quickly unsuccessful rational traders should quit. We present evidence of remarkable trading persistence in the face of losses, for example, over half of day-trading volume is generated by experienced, unsuccessful day-traders. The reader must assess for him or herself whether this perverse persistence is due to biased prior beliefs, biased learning, or both.

The rational learning models predict that speculators will start by placing small trades. Successful speculators will increase their trade sizes, unsuccessful traders will not. Thus—irrespective of prior beliefs—the rational learning models predict our second null hypothesis:

H2: Day traders with previous net losses will not increase their trade sizes.

Under Gervais and Odean's biased learning model, it is possible for unsuccessful traders to become overconfident, and more active traders, if their learning bias is sufficient. Thus an increase in trade size by unprofitable day-traders is contrary to the rational learning models but consistent with biased learning.

II. Data and Methods

II.A. Day Traders and Speculative Trading

Empirical tests of the learning models must identify traders who trade speculatively. Investors might reasonably trade to save (or consume), to rebalance their portfolios, or to reduce their tax liability. Thus, an important feature of our empirical strategy is to identify a clean sample of speculators. We do so by focusing on day trading on the Taiwan Stock Exchange. Day trading is the purchase and sale of the same stock by an investors on a day. We argue that these intraday trades are almost certainly speculative. Moreover, day trading is common and prevalent in Taiwan.

We are not the first to study day trading, though the sample of day traders we study is much large and the time-series much longer than those in prior studies.[†] The one exception to this generalization being Barber, Lee, Liu, and Odean (2010) who identify a small subset of day traders (less than 1% of the day trading population) predictably earn

[†] Harris and Schultz (1998) study SOES bandits at two brokers. Garvy and Murphy (2002, 2005) analyze 15 and 1,386 day traders at one US broker. Seasholes and Wu (2004) analyze the trades of 10 active traders on the Shanghai Stock Exchange. Linnainmaa (2003) analyzes 7,686 Finnish day traders.

profits. None of these prior studies used the empirical setting to test rational and biased models of learning, the focus of our investigation.

II.B. 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.[‡] 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 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. During our study period, 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.

Since our analysis focuses on day trading, an important consideration is transaction costs. The TSE caps commissions at 0.1425% of the value of a trade. Some brokers offer lower commissions for high-volume traders. Officials at brokerage firms and the TSE indicated to us that the largest commission discount offered is 50% (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. We use the 10 basis points when calculating returns net of fees. Taiwan also imposes a transaction tax on stock sales of 0.3%.

[‡] 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 December 2000, Saturday trading occurred from 9 am to noon. From 2001 on, there has been no trading on Saturday.

II.C. Trades Data and Descriptive Statistics

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.

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. In total, the dataset contains 3.7 billion purchase (or sale) transactions with a value of $NT 310 trillion (approximately $10 trillion US).[§] 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 of which is 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 $(½*P_b*min(S_b,S_s)+$

[§] 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.

[**] Many corporations are small firms that are majority or wholly owned by an individual. Thus, the corporate category of trader also includes thousands of individual investors who trade under the label of corporation.

$\frac{1}{2} * P_s * min(S_b, S_s)$). Over our sample period, day trading accounted for more than 17% of the total dollar value of trading volume. Most day trading (about 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).

Virtually all day trading can be traced to individual investors. In the average month, individual investors account for over 99% of all day traders (and 95% of day trading volume). 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. In contrast to U.S. markets, dealers are not active providers of liquidity. TSE rules state that 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," yet 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 individual investors.

In Figure 1, we plot day trading as a percentage of total trading volume and the number of individuals who day trade by month. While day trading was somewhat less prevalent in the early part of our sample period (perhaps because of the liberalization of margin short selling which occurred at the end of 1993), the share of volume traced to day trading has been consistently around 20% of total trading volume from 1994 to 2006. 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% of the adult population day trades in the average month. In terms of both a percentage of total trading volume and numbers of traders, day trading is an equilibrium feature of the Taiwan stock exchange with no apparent trend over the from 1997 through 2006.

II.D. Performance Measurement

Our performance measurement focuses primarily on the intraday profits of all trades made by day traders and on trade-weighted intraday returns. 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 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 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 (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 10 bps round-trip commission and a 30 bps transaction tax on sales. (See appendix for details.)

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,[††] it is important to include both round-trip and other trades when analyzing performance.

[††] Barber, Lee, Liu, and Odean (2007) and Linnainmaa (2005) document, respectively, that individual Taiwanese investors and Finnish day traders exhibit the disposition effect.

Finally, we calculate the long-run (interday) returns to open positions. Positions for each investor are built from their prior trades.[‡‡] This return on the remaining portfolio includes the returns earned on trades that close positions and the transaction costs associated with those trades. We calculate the total returns earned by day traders by taking a weighted average of the returns on day trades and the remaining portfolio; the weights assigned to the two portfolios are the total value of day trading (i.e., the value of long buys plus the value of short sells on that day) and the total value of open positions at the close of the prior trading day, respectively.

In Figure 2, 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 risk-free 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.

III. Aggregate Performance Results

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.

[‡‡] Some errors inevitably occur 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.

There are two reasons that including all trades in the month of day trading might positively bias our performance analysis. First, due to the disposition effect, day traders are more likely to close profitable positions. 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. (In subsequent analyses, we identify day traders ex-ante to avoid these issues.) We are not concerned by these biases in this preliminary analysis since we document poor performance in aggregate.

In the second column of Table 1, we present the gross performance of day traders. On average, day traders lose 9.9 basis points on their day trading before costs (t=-12.38). Trading costs more than double the losses to 24.9 basis points per day. Moreover, we observe reliably negative gross and net performance in all years but 1992. The net return on the remaining portfolio (i.e., open positions) and the total net portfolio return are presented in the last eight columns of Table 1. The remaining portfolio also earns a negative alpha, so the total profits of day traders are negative.

In aggregate, day trading is a losing proposition; 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, most must either be overconfident about their prospects of success or derive non-financial utility from 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 and explicitly test rational learning models after presenting results on cross-sectional variation in performance.

III.A. Rational and Behavioral Learning Models: Confirming Evidence

A. 1. Survival and Quitting

We begin by estimating the survival rate of day traders. Our trading data starts in 1992. To reasonably ensure that we are analyzing new day traders, we restrict our analysis to those who begin day trading after 1992. Our data ends in 2006 and thus is right-censored. We consider a trader to have quit day trading if we observe no day trading for 12 consecutive months. As a result of this requirement, we do not analyze day traders who begin day trading in 2006 since we cannot reliably observe whether they have quit.

In Figure 3, we present two five-year Kaplan-Meier survival functions. In one, we consider the survival of all day traders and consider their first month of day trading as their entry month. In the second, we consider the survival of heavy day traders – those who have day traded for at least 20 days – and consider the first month when they hit the minimum 20-day threshold as their entry month.

Among all day traders, nearly 40% day trade for only one month. Within three years, only 13% continue to day trade. After five years, only 7% remain. For heavy day traders, survival is much more persistent. Only 5% drop out within one month, while survival rates at three and five years are 36% and 23% respectively.

To test whether past profitability affects the decision to quit day trading, we estimate the following Cox proportional hazard rate model, $h(t,x) = h_0(t)e^{\{XB\}}$, where X is a matrix of independent variables, B is a vector of coefficient estimates, $h_0(t)$ is the baseline hazard rate (i.e., the hazard rate when all covariates are equal to zero), and $h(t,x)$ is the hazard rate conditional on a set of covariates (x) at time t. In our application, a trader becomes at risk of quitting once he begins day trading.

To ensure that we have a reasonable measure of a trader's past performance, we restrict our analysis to heavy day traders – those who have day traded for a minimum of 20 days. To assess the impact of past performance on quitting, we use the Sharpe ratio of day trading returns defined as the mean daily return divided by the standard deviation of the daily day trading return. (Results are qualitatively similar if we use the Sharpe ratio of dollar profits.) To estimate the impact of past profits on the propensity to quit day trading, we construct a series of 15 dummy variables corresponding to the following ranges: $(-\infty, -0.15]$, $(-0.15, -0.10]$, … , $(0.10, 0.15]$, $(0.15, \infty)$. When estimating the Cox proportional hazard rate model, we set the range $(0, 0.05]$ as the default category and include the remaining 14 dummy variables as covariates in our estimation. As control variables we include measures of past day trading activity: the log of the number of days with day trading activity (frequency), the log of the number of days since a trader's first day trade (experience), and the log of the total volume of day trading (volume). In the event history analysis, all independent variables are updated monthly.

The results of this analysis are presented in Figure 4. The horizontal axis of the figure represents profit categories, while the vertical axis represents the hazard rate relative to the omitted profit category (with Sharpe ratios that range from (0, 0.05]). As predicted by the learning models, the Sharpe ratio of profitability is negatively related to the hazard rate. More profitable day traders are less likely to quit.[§§]

However, the effect is not linear. The propensity to quit is relatively insensitive to past Sharpe ratios in the domain of gains (i.e., for Sharpe ratios greater than zero). In fact, among the top three past profit categories, the proportional hazard rate is not reliably different from one. With a positive signal about one's trading ability, there is little incentive to quit regardless of the strength of that signal.

The propensity to quit is quite sensitive to the magnitude of losses. A day trader with just negative past performance (a Sharpe ratio between -0.05 and 0), is a modest 4%

[§§] The relation between profits and the propensity to quit is similar regardless of whether we include control variables. However, the control variables are all reliably related to hazard ratios at the 1% significance level. Frequent day traders are less likely to quit; a one standard deviation increase in the frequency of past day trading reduces the hazard rate to 0.55. Experienced day traders are less likely to quit; a one standard deviation increase in experience reduces the hazard rate to 0.67. Heavy day traders are more likely to quit; a one standard deviation increase in past day trading volume increases the hazard rate to 1.12. Overall, these results indicate that large unprofitable and infrequent day traders with little experience are the most likely to quit day trading.

more likely to quit than a day trader with just positive performance (a Sharpe ratio between 0 and 0.05, the default category). The effect of profits on the decision to quit is not linear in losses. For example, consider the impact on hazard rates of moving across three equidistant profit categories: (0, 0,05], (-0.20, -0.15], and (-0.40, -0.35]. The first move, from just profitable to the midrange of losses increases the hazard rate by 12 percentage points (from 1.00 to 1.12); the second move, from the midrange of losses to steep losses, increases the hazard rate by an additional 14 percentage points (from 1.12 to 1.36).

In summary, these analyses provide strong evidence that traders learn about their own ability by trading. Those who profit are less likely to quit, though the effect is most pronounced for those with steep losses.

A. 2. The response of trading to performance

A second prediction of the learning models is that traders will increase their trading intensity in response to positive signals about their ability. To test this prediction, we analyze changes in day trading. In each month, we calculate the total dollar volume of day trading for each day trader. We then calculate the ratio of day trading in month *t* to that in month *t-1*. Our analysis is based on the log of this ratio so as to mitigate the influence of outliers. The log-ratio can be roughly interpreted as the percentage change in day trading between month *t-1* and *t*. We also condition on the presence of day trading in both months *t* and *t-1*, so our analysis is conditional on the decision to continue day trading. In addition to changes in trading volume, we also analyze the proportion of day traders that increase their day trading from month *t-1* to *t*.

We split day traders based on their past profitability net of transaction costs. Specifically, we define profitable traders as those who earn a mean net daily return greater than zero through month *t-1*. We also split traders based on their prior experience into four broad categories: (1) < 1 year, (2) 1 to 3 years, (3) 3 to 5 years, and (4) more than 5 years, where experience is measured as months since a traders first day trade.

The results of this analysis are presented in Table 2. Among all traders, profitable traders increase their day trading more than unprofitable day traders. The log-ratio of volume if 5.33% for profitable day traders and 0.09% for unprofitable day traders; the difference in the two ratios is highly significant.

The response of trading to performance also varies with trader experience. For the rookie traders (those with less than 12 months of experience), the differences between profitable and unprofitable day traders are nearly double those of all day traders. This observation is generally consistent with the learning models as day traders are likely to learn the most about their ability during their early experience.

In panel B, we present the proportion of day traders who increase day trading from month t-1 to month t. The same broad patterns that we document are also observed in panel B. However, it is noteworthy that these differences, though statistically significant, are not economically large.

III.B. Rational Learning Models: Disconfirming Evidence

To this point, we find broad support for the rational and behavioral learning models of investor behavior. Poor performers quit and trading increases following strong performance. The confirming evidence indicates learning is an important feature of financial markets. In this section, we argue that rational learning does not explain behavior of the large population of speculative investors for three reasons: aggregate performance is negative, experienced speculators lose money, and unprofitable speculators persist.

B. 1. Aggregate performance is negative

We begin by noting that the aggregate performance of day traders is negative (see Table 1). Even the heaviest day traders lose money (see Table 2). While we would not expect all, or even most, speculators to profit in a learning equilibrium, we would expect the aggregate performance of speculators to be positive if the number of new entrants into the market for day trading is stable over time.

To see the logic behind this assertion, consider the following simple, concrete, example. Suppose that 21 new speculators try trading each year. Only one of these has skill; 20 are unskilled. Unskilled speculators trade for one year, lose \$1, and quit. Skilled speculators trade for 10 years, earn \$1 each year and quit. Thus aggregate speculator profits each year are -\$10. Because skilled speculators stay in the market longer, skilled speculators account for a greater fraction of active speculators (i.e., 10/30) than of new speculators (i.e., 1/21). Expected lifetime profits for a new speculator are $(1/21)\$10 + (20/21)(-\$1) = -\$0.476$. Note that aggregate annual profits divided by the number of new speculators each year are equal to expected lifetime profits (i.e., -\$10/21 =-\$ 0.476) and that aggregate annual profits divided by the number of all speculators trading in a year (e.g., -10/30 = -\$ 0.333) are of the same sign but lower magnitude than expected lifetime profits. Thus, when aggregate profits are negative, they provide an upper limit to the expected lifetime profits of a speculator.

Consequently, the strong and persistent losses that we document for day traders are not consistent with a rational learning model in which risk-averse or risk-neutral investors try their hand at speculation in order to ascertain their ability. For day traders, “trading to learn” has a lower expected lifetime return and a greater variance than buying and holding the market portfolio.

B. 2. Experienced Day Traders lose money

A central feature of the learning model is the observation that bad traders quit. This raises two natural questions. First, do we observe long-lived day traders with a history of losses? Second, what fraction of day trading can we trace to traders with a history of losses?

To investigate the relation between experience and performance, we categorize day traders into groups based upon the number of months in which they day trade. We then analyze the performance for each subgroup. The results of this analysis are presented in Table 3.

The most experienced day traders have the best performance. This is not at all surprising as this analysis clearly suffers from a survivorship bias. However, what is informative is the observation that experienced day traders – those with as much as ten years of experience – still register losses. This suggests that day traders continue to trade even when they receive a negative signal regarding their ability.

B. 3. The Persistence of Unprofitable Day Traders

The learning model predicts that day traders who experience losses will quickly realize the folly of their ways and cease trading. Presumably, if unbiased learning were the major dynamic explaining the presence of losing day traders, most of the losing traders would be relative neophytes with only a short history of losses. To see if this is indeed the case, we estimate the fraction of day trading that can be traced to day traders with a history of losses.

To do so, we identify four groups of day traders: (1) First Timers, (2) Occasional Day Traders, (3) Unprofitable Day Traders, and (4) Profitable Day Traders. We begin by first identifying all traders who did not begin day trading until 1993. We then allow two years, 1993 and 1994, for traders to build up a history of day trading. We then categorize day traders at the beginning of year *t* (*t=1995, 2006*) based on their prior day trading activity and profits cumulatively through year *t-1*. First timers are those with no prior experience of day trading through year *t-1*. Occasional day traders are those with less than 20 days of day trading experience or a 12-month day trading hiatus at the end of year *t-1*. Unprofitable (profitable) day traders have a minimum of 20 days of day trading experience and a negative (positive) mean daily day trading return net of costs through year *t-1*.

The results of this analysis are presented in Table 4. In panel A of the table, we base proportions in each category on the number of day traders; in panel B, the proportions are based on the dollar volume of day trading. Profitable day traders make up a small proportion of all traders – 1.6% in the average year (see last row, panel A). However, these day traders are very active – accounting for 12% of all day trading activity in the average year (last row, panel B). The vast majority of day traders are first timers or occasional day traders. Combined, these categories represent over 70% of all day traders in the average year, though these day traders represent only 34% of total day trading volume. Unprofitable day traders represent nearly a quarter of the day trading population, but represent over half of all day trading activity. Thus, many day traders are remarkably persistent in their day trading activity despite a history of losses and do not appear to be rationally learning about their ability.

IV. Discussion

Our data are remarkably well suited for testing models of rational learning such as Mahani and Bernhard's. Mahani and Bernhard write that their "prototypical novice speculator is the Japanese hairdresser Kiyoshi Wakino" who day trades between giving haircuts (p. 1317). We observe the day trading of hundreds of thousands of investors over a seventeen-year period. And while our day traders are Taiwanese and certainly not all hairdressers, it is probable that—like Kiyoshi Wakino—many of our novice day traders pursue trading in addition to, if not during, a regular job. Despite the size and appropriateness of our data, our results simply do not support the rational learning models. In Mahani and Bernhard's model, day trading is, in aggregate, profitable because skilled day traders are able to take advantage of the insensitivity of liquidity traders to price and the willingness of competitive market-makers to forego a profit. In Taiwan, day traders, in aggregate, lose money. Therefore it is not rational for a risk-averse investor with no special claim to superior ability to undertake day trading in hopes of discovering that he is amongst the chosen few. Furthermore, it is not rational for day traders who have incurred persistent losses to continue day trading for the purpose of learning about their ability.

So why do investors take up day trading and why do so many persist in the face of losses? We consider three broadly defined answers to this question.

First, it could be the case that day traders do not have standard risk-averse preferences; they may be risk-seeking or attracted to investments with highly skewed investments, such as lotteries, that have negative expected returns but a small probability of a large payoff as suggested by Kumar (2009). However, the day trading profits that we document are similar in magnitude to, and far less prevalent than, the 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. Furthermore, daily day trading returns have a negative mean, and yet lower variance and less right-hand skewness than the average Taiwanese stocks. Define the annual day trading return as the sum of the returns earned on each day of day trading. For traders with a minimum of ten days of day trading, the skewness of the annual return is -0.22 (i.e., modestly negatively skewed). In contrast, when we calculate the skewness of annual returns across individual stocks listed on the TSE from 1981 to 2009, the coefficient of skewness is positive in all but one year and averages 2.36. Thus, a risk or lottery seeker could better maximize his utility, with far less effort, by simply buying and holding a single volatile stock.

Second, day traders may be overconfident in their prior beliefs about their abilities and biased in the way they learn. 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 novice 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. Once investors undertake day trading, their prior overconfidence may be reinforced through biased learning as in Gervais and Odean (2001). Furthermore, heavy day traders, who earn gross profits but net losses, may not fully consider trading costs when assessing their own ability.

Third, day traders may trade for non-financial motivations including entertainment, a taste for gambling, and the desire to impress others (see, e.g. Grinblatt and Keloharju (2009)). Some investors may enjoy the process of day trading so much that they are willing to persist in the face of regular losses. Some investors may be attracted to the casino like qualities of day trading with its frequent bets, wins, and losses.[***] Some investors may choose to day trade in hopes of impressing others.[†††]

We are unable to explicitly test whether day traders are motivated by overconfidence rather than the desire for entertainment, gambling, or to impress others. Nor is there reason to believe that overconfidence and non-financial motivations are mutually exclusive. Quite to the contrary, entertainment, gambling, and the desire to impress others are all likely to be more attractive reasons to trade if one is overconfident about one's likelihood of success.

In Mahani and Bernhard's model, "*all* speculators are made worse off if some speculators are *slightly* overconfident" (p. 1315). Our results are consistent with this prediction. If heavy day traders persist in trading due to overconfidence, then that overconfidence is detracting from their own welfare and that of other speculators. The welfare of the heavy traders themselves is diminished because, on average, they earn net losses; the welfare of other speculators is diminished because, on average, heavy traders earn gross profits thereby reducing the average returns of other investors. The beneficiaries of this overconfidence are brokerage firms—through commissions—and the government—through the transaction tax.

V. Conclusion

We test predictions of models of learning by rational traders and find clear evidence that the decision to continue or increase day trading is influenced by previous day trading returns. Nevertheless, rational models of learning do not explain all or even most day trading. The most experienced day traders lose money and over half of all day trading can be traced to traders with a history of losses. Persistent trading in the face of losses is inconsistent with models of rational learning. So, too, is the decision to try day

[***] Kumar (2009) shows a correlation between the propensity to gamble and the types of investment decisions U.S. investors make. Barber, Lee, Liu, and Odean (2008) document that the introduction of a National Lottery in Taiwan coincided with a significant drop in trading volume on the Taiwan Stock Exchange. Grinblatt and Keloharju (2009) document that investors prone to sensation seeking trade more frequently.

[†††] Several papers argue that investment decisions are influenced by social concerns, for example, Barber, Heath, Odean (2003), Statman (2004), and Hong and Kacperczyk (2009).

trading when ex-ante expected lifetime profits are negative. For prospective day traders, "trading to learn" is no more rational or profitable than playing roulette to learn.

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APPENDIX: 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:

$$r_{gt} = \frac{\sum_i \sum_j \left(S^L_{ij\,t} - B^L_{ij\,t}\right) + \left(S^S_{ij\,t} - B^S_{ij\,t}\right)}{\sum_i \sum_j \left(B^L_{ij\,t} + S^S_{ij\,t}\right)}, \tag{A1}$$

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 $\left(S^L_{ij\,t}\right)$ 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 $\left(B^S_{ij\,t}\right)$ 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, though 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:

$$r_{gt}^{net} = \frac{\sum_i \sum_j \left(S_{ij\,t}^L - B_{ij\,t}^L\right) + \left(S_{ij\,t}^S - B_{ij\,t}^S\right) - c_b * \left(B_{ij\,t}^L + B_{ij\,t}^S\right) - c_s\left(S_{ij\,t}^L + S_{ij\,t}^S\right)}{\sum_i \sum_j \left(B_{ij\,t}^L + S_{ij\,t}^S\right) + c_b B_{ij\,t}^L + c_s S_{ij\,t}^S}, \qquad \text{(A2)}$$

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 10bps in commissions and 30 bps in transaction tax) less than the gross return (2.50%). The shortfall is slightly greater than 50 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:

$$rp_{gt} = \frac{\sum_i \sum_j \left(V_{i,j,t}^L - V_{i,j,t-1}^L\right) - \left(V_{i,j,t}^S - V_{i,j,t-1}^S\right)}{\sum_i \sum_j \left(V_{i,j,t-1}^L + V_{i,j,t-1}^S\right)}, \qquad \text{(A3)}$$

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 basis points. For short positions, stocks bought to cover shorts on day are valued at the purchase price less an assumed transaction cost of 5 basis points.

Finally, the total portfolio return on day t for group g is calculated as the weighted average of the intraday return net of fees and the remaining portfolio return, where the weights are determined by the denominators in equations A2 and A3.

Table 1: Performance for Sorts based on Prior

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. The total net portfolio return combines the net day trading return and the remaining portfolio net return; alphas are calculated relative to the close-to-close market return. The last column presents the percentage of all trades that are round-trip day trades.

	Returns to Day Trading						Remaining Portfolio Net Return				Total Portfolio Net Return				Day Trade / All Trade
	Gross		Net												
	α (%)	*t-stat*	α (%)	t-stat	Beta	R-Sq	α (%)	*t-stat*	Beta	R-Sq	α (%)	*t-stat*	Beta	R-Sq	
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: Changes in Day Trading Conditional on Experience and Past Profitability

Day trading is defined as round-trip trades by the same stock/investor/day. We calculate the total dollar volume of day trading in each month for each investor (D_{it}). We calculate the ratio of day trading in month t to day trading in month t-1. In panel A, we present the mean of the log ratio, $ln(D_{it}/D_{it-1})$, for trader groups based on experience (x) groups (rows) and profit categories (columns). In Panel B, we present the proportion of day traders that increase day trading from month t-1 to month t for each group. Profitable day traders are those with a mean daily returns net of fees are positive through month t-1.

	Unprofitable Trader		Profitable Traders		
	Mean	N	Mean	N	t-test (difference in means)
Experience (X) Partition	Panel A: Log-ratio of Day Trading in month t and month t-1, $\ln(D_{it}/D_{it-1})$				
All Traders	0.09%	8,076,229	5.33%	1,022,271	-41.01
X <= 1 yr	2.70%	1,879,740	11.34%	343,635	-36.39
1 yr < X <= 3 yr	-1.46%	2,204,125	3.09%	256,209	-17.88
3 yr < X <= 5 yr	-0.63%	1,579,379	2.62%	166,856	-10.51
5 yr < X	-0.06%	2,412,985	1.26%	255,571	-5.44
	Panel B: Percentage of Day Traders that Increase Trading from month t-1 to month t				
All Traders	49.77%	8,076,229	51.38%	1,022,271	-30.61
X <= 1 yr	50.32%	1,879,740	53.00%	343,635	-28.93
1 yr < X <= 3 yr	49.31%	2,204,125	50.76%	256,209	-13.97
3 yr < X <= 5 yr	49.63%	1,579,379	50.59%	166,856	-7.46
5 yr < X	49.87%	2,412,985	50.33%	255,571	-4.46

Table 3: Performance of Day Traders based on Ex-Post Survival, 1993 to 2006

Day Traders are grouped based upon the length of time between their first and last day of day trading within between 1993 and 2006. We do not include those who day traded in 1992 to increase the likelihood that a first observed trade in our dataset is the first day trade engaged in by the investor. The alphas are estimated using the following regression of daily returns: (Rpt - Rft) = αp + βp(Rmt - Rft) + εpt, 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				Day Trade / All Trade	Share of Day Trading
	Gross		Net													
	α (%)	t-stat	α (%)	t-stat	Beta	R-Sq	α (%)	t-stat	Beta	R-Sq	α (%)	t-stat	Beta	R-Sq		
< 3 Mths	-0.147	-15.41	-0.215	-22.61	0.31	40%	0.052	6.99	0.94	91%	-0.006	-0.86	0.82	91%	3.0%	1.3%
3 to 6 Mths	-0.169	-18.23	-0.255	-27.60	0.31	40%	0.010	1.50	0.93	93%	-0.039	-6.54	0.84	92%	7.7%	2.3%
6 to 12 Mths	-0.179	-19.99	-0.281	-31.56	0.30	42%	-0.006	-0.93	0.92	93%	-0.049	-8.74	0.85	93%	12.3%	6.2%
1 to 2 Years	-0.180	-20.61	-0.300	-34.57	0.30	42%	-0.010	-1.83	0.92	94%	-0.052	-9.52	0.85	94%	17.3%	13.4%
2 to 3 Years	-0.161	-19.04	-0.295	-35.00	0.29	42%	-0.011	-1.84	0.91	94%	-0.048	-8.34	0.86	93%	21.3%	12.7%
3 to 5 Years	-0.138	-16.63	-0.280	-33.99	0.28	42%	-0.013	-2.47	0.92	95%	-0.048	-9.30	0.87	95%	24.1%	20.8%
5 to 10 Years	-0.089	-11.05	-0.241	-30.10	0.27	42%	-0.009	-1.79	0.94	95%	-0.039	-7.97	0.89	95%	27.5%	31.9%
> 10 Years	-0.011	-1.39	-0.169	-21.14	0.27	41%	0.004	0.75	0.96	96%	-0.023	-4.95	0.91	96%	29.4%	11.4%

Table 4: Day Trading by Occasional Traders, First Time Traders, Unprofitable Traders, and Profitable Traders

Occasional day traders are those with less than 20 days of day trading or a one year break in day trading. First timers are day traders who started within the calendar year. Unprofitable (profitable) day traders have a minimum of 20 days of day trading experience through year t-1 and a negative (positive) mean daily day trading return net of costs.

Year	Occasional Traders	First Timers	Unprofitable Traders	Profitable Traders	All Traders
	Panel A: Percentage of All Traders				Number
1995	47.6	41.1	10.4	0.9	136,879
1996	46.1	38.0	14.8	1.1	146,109
1997	32.4	58.5	8.6	0.5	354,057
1998	42.3	40.3	16.5	0.9	399,407
1999	43.7	33.4	21.8	1.1	416,815
2000	42.0	35.5	21.3	1.2	519,343
2001	45.5	24.8	27.7	2.0	430,638
2002	44.0	25.7	28.2	2.1	465,378
2003	42.6	19.7	35.3	2.4	386,450
2004	43.1	22.8	32.1	1.9	431,908
2005	40.6	16.1	40.7	2.6	305,777
2006	45.0	18.9	34.1	2.0	357,877
Mean	42.9	31.2	24.3	1.6	362,553
	Panel A: Percentage of Day Trading Volume				$ Volume of Day Trading ($NT Tril.)
1995	34.2	20.5	38.0	7.3	826
1996	28.0	19.9	43.7	8.3	967
1997	26.4	35.6	31.2	6.7	5,017
1998	24.2	18.5	45.6	11.7	4,363
1999	23.1	13.7	49.9	13.3	3,596
2000	20.8	12.7	52.5	14.1	4,010
2001	18.8	8.7	55.8	16.7	2,880
2002	17.2	7.8	59.7	15.4	3,040
2003	14.6	5.9	65.2	14.3	2,462
2004	14.7	6.5	65.7	13.1	2,647
2005	12.8	4.9	70.2	12.1	2,113
2006	13.4	4.9	70.9	10.8	2,662
Mean	20.7	13.3	54.0	12.0	2,882

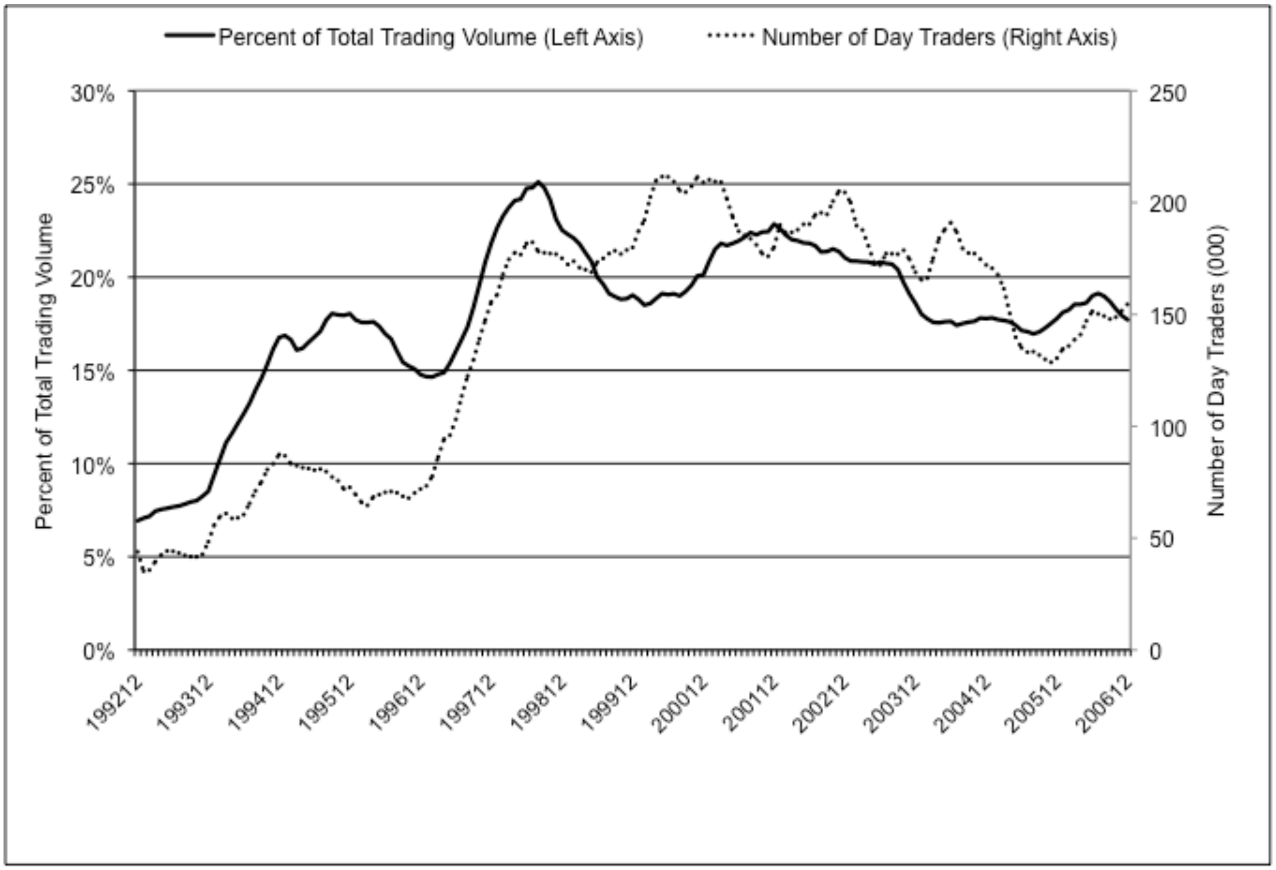

Figure 1: Day Trading as a Percent of Total Volume and **Number of Individual Day Traders**

The figure presents the 12-month moving average for (1) the number of individual investors who engage in day trading and (2) day trading as a percent of total trading volume.

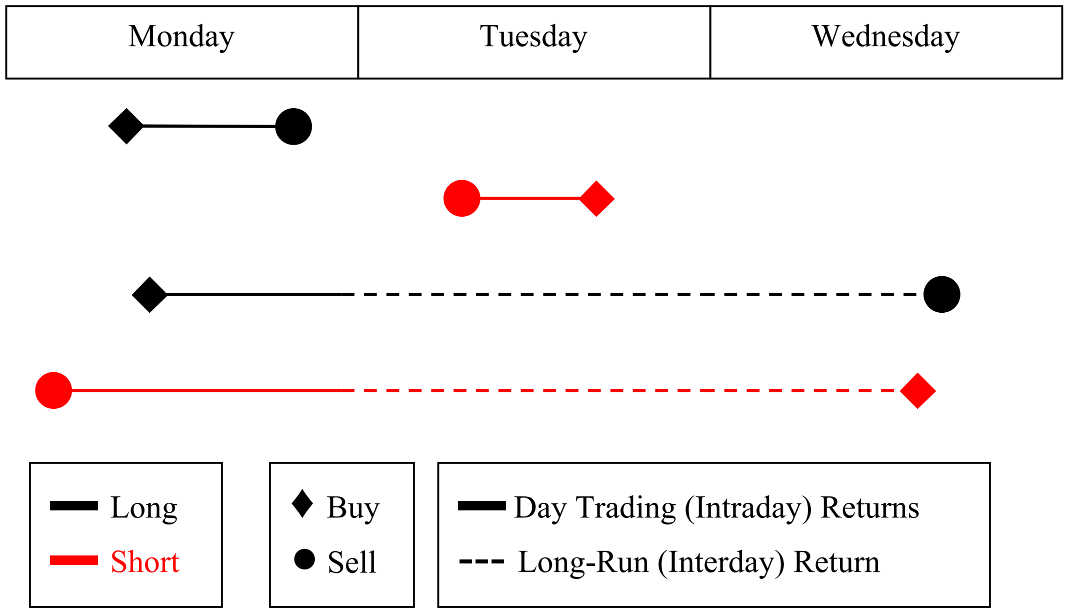

Figure 2: Example of Trading Activity for a Day Trader

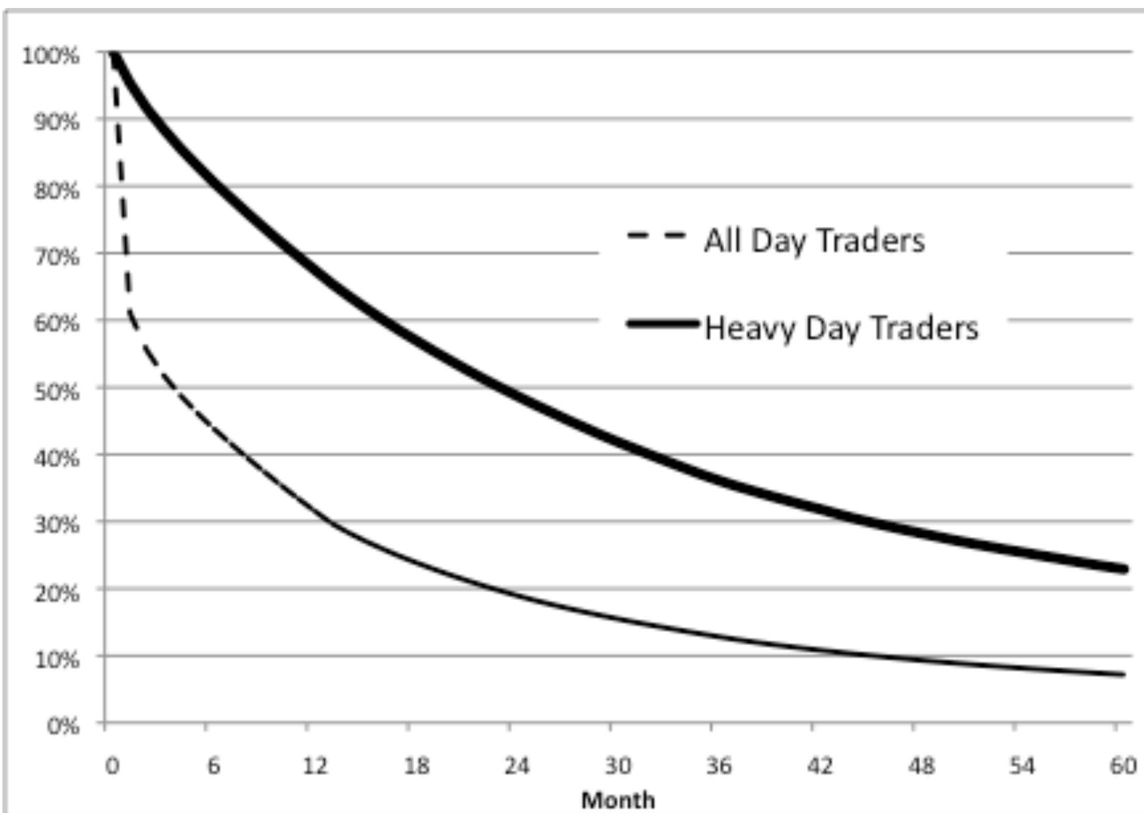

Figure 3: Day Trading Survival Function for All Day Traders and Heavy Day Traders. Entry for all day traders is first month of day trading, while entry for heavy day traders is first month when day trader has engaged in day trading for 20 days.

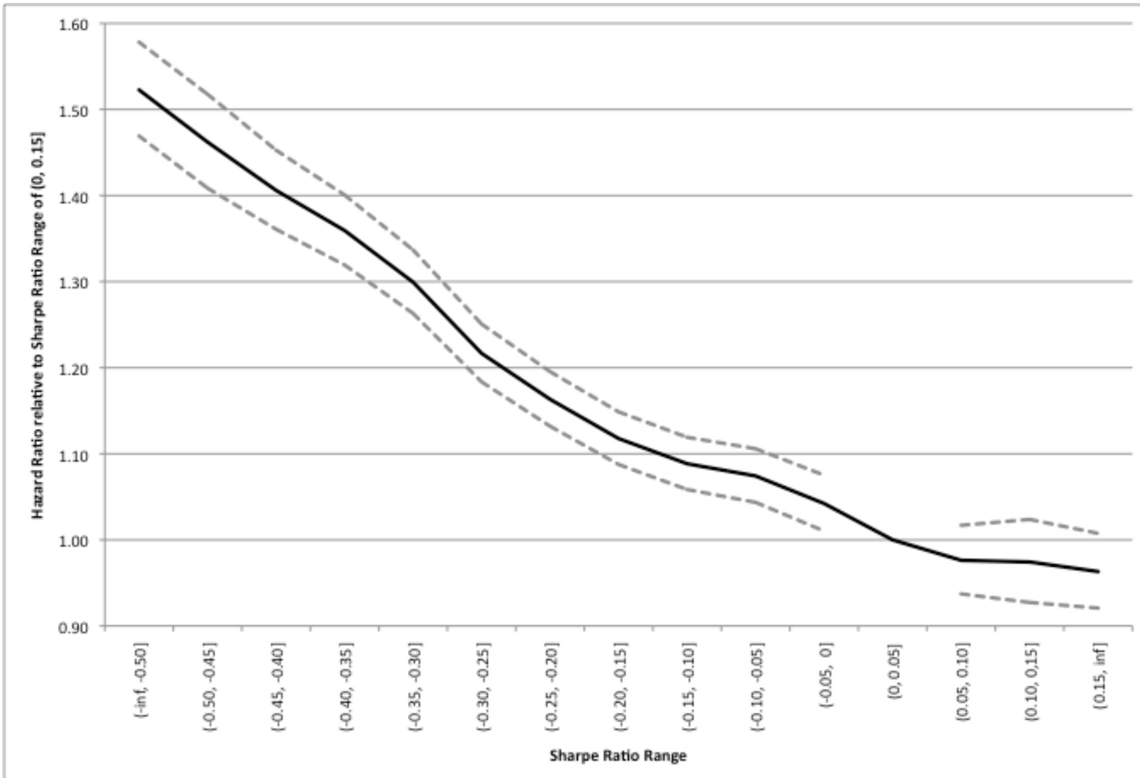

Figure 4: Hazard Ratio for Quitting Day Trading Conditional on Past Profitability. Observations are monthly. Traders are considered to have quit day trading in the first month for which we observe no day trading in twelve consecutive months. The figure reports the hazard ratio for quitting and the 95% confidence interval (dashed lines) for different profit categories relative to the default category of (0, 0.05] where the hazard ratio is equal to one by construction. The sample consists of day traders with a minimum of 20 days of day trading. The entry month is the first month when they exceed 20 days of day trading. Profits are measured using the Sharpe ratio of returns -- the mean daily return divided by the standard deviation of daily return. The Cox proportional hazard rate model includes controls for past day trading activity: the frequency of day trading (the log of the number of days with day trading), the volume of day trading (the log of day trading volume), and experience (the log of the number of days of day trading).