Learning Fast or Slow

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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 superior trading ability. Consistent with models of both rational and biased learning, we document that unprofitable day traders are more likely to quit than profitable traders. Inconsistent with models of rational speculation and learning, we document that the aggregate performance of day traders is negative, the vast majority of day traders are unprofitable, and many persist despite an extensive experience of losses.

In rational learning models (Mahani and Bernhardt (2007), Linnainmaa (2010), Lubensky (2017)), investors 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 their abilities 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 their abilities 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 (more that 75% 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. Using Indian data, Campbell, Ramadorai, and Ranish (2014) document experienced investors generally behave in a manner consistent with the recommendations of finance theory. 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), Linnainmaa (2010), and Lubensky (2017) 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 traders persist after extended periods of losses. In one analysis spanning 1993-2005, we analyze how past performance affects traders willingness to continue. Specifically, we sort traders based on the number of days they have engaged in day trading as of the end of the previous month and on the past profitability of their intraday trades net of trading costs. To have an accurate measure of day trading experience, we exclude traders who day traded in 1992. Previously unprofitable traders with 50 or more days of past day trading experience have a 95.3% probability of day trading again in the next 12 months, while previously profitable traders with 50 or more days of past day trading experience have a 96.4% probability doing so. So, not only do experienced day traders with histories of losses

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persist in day trading, they do so at nearly the same rate day traders who have been profitable.

In a second analysis, we document the 97% of day traders and over 90% of day trading volume can be traced to investors with predictable losses based on their past experience and performance. Specifically, we sort day traders into six groups based on their past experience. Within each experience group, we further partition investors based on whether their past profits net of trading costs are positive or negative. Thus, we are left with 12 groups based on the double-sort of past experience and past profitability. Among these 12 groups, only the profitable and most experienced investors predictably earn future profits net of trading costs. However, these investors represent less than 3% of all day traders and less than 10% of all day trading volume. Put differently, 97% of day traders can expect to lose money from trading and more than 90% of all day trading volume can be traced to investors who predictably lose money.

Our research fits into the large literature on the behavior and performance of individual investors. Several papers document that individual investors hurt their performance by trading. Odean (1999) analyzes trading at a large discount broker and documents the stocks bought by individuals underperform the stocks sold. Barber and Odean (2000, 2001) analyze the positions of investors at a large discount broker and document they earn reliably negative returns mostly because of trading costs. Grinblatt and Keloharju (2000) document individual investors underperform in Finland, which Linnainmaa (2010) argues is mostly a result of unmonitored limit orders. Barber, Lee, Liu, and Odean (2009) document underperformance for all individual investors in Taiwan.[1]

While there are host of sensible reasons to trade (e.g., a need for liquidity or portfolio rebalancing), the studies cited above generally conclude the majority of observed trade is speculative. Thus, the documented underperformance of individual investors raises the question of why individual investors trade speculatively and poorly.

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[1] Kaniel, Saar, and Titman (2008), Barber, Odean, and Zhu (2009), Kelley and Tetlock (2013), and Boehmer, Jones, and Zhang (2017) use different datasets, but all three studies document the buy imbalance of retail investors positively predicts stock returns at short horizons (up to one week) in the U.S. Barber, Odean, and Zhu (2009) document reversals at longer horizons, while Kaniel, Saar, and Titman (2008), Kelley and Tetlock (2013), and Boehmer, Jones, and Zhang (2017) do not find evidence of reversals.

Three prominent explanations for the deleterious trading of individual investors have emerged in the literature: overconfidence, entertainment, and learning.

In theoretical models of overconfidence, overconfident traders trade too much and to their detriment (Odean (1998), Gervais and Odean (2001), Caballe and Sakovics (2003)).[2] Consistent with the predictions of these models, investors who trade most perform worse (Barber and Odean, 2000). Glaser and Weber (2007) match survey data to trading records for individual investors and document investors-based scores of overconfidence correlate with trading activity. Biais, Hilton, Mazurier, and Pouget (2005) use an experimental asset market to document calibration-based overconfidence reduces trade performance, and Deaves, Luders, and Luo (2008) provide experimental evidence that calibration-based overconfidence induces additional trade.

Perhaps investors engage in losing trades because it's entertaining. Several bits of empirical evidence support entertainment motives as a mechanism that generates trade. Dorn and Sengmueller (2009) match survey responses and administrative records at a German broker and document investors who report enjoying investors or gambling have twice the turnover rates of their peers. Grinblatt and Keloharju (2009) conjecture that investors trade as a form of sensation seeking. To test this conjecture, they document that investors with more speeding tickets tend to trade more aggressively. Moreover, the introduction of a national lottery in Taiwan reduced trading by individual investors (Barber, Lee, Liu, and Odean (2008), Gao and Lin (2014)). Dorn, Dorn, and Sengmueller (2015) provide similar evidence using multistate U.S., California, and German lotteries.

In theory, learning provides a rational explanation for speculative trading as modeled in Mahani and Bernhardt (2007) and Linnainmaa (2011). Mahani and Bernhardt (2007, p.1334) conclude that their model indicates "Most inexperienced traders realize losses, conclude that they are unlikely to be skilled, and leave the markets; survivors expand their trades and make more profits. Learning produces the aggressive trading that is traditionally attributed to psychological biases." Linnainmaa (2011, p.163) writes "… a stylized learning model approximates household trading decision remarkably well." Seru et. al. (2010) similarly argue that traders learn from experience and, as a result, trading

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[2] In related work, Daniel, Hirshleifer, and Subrahmanyam (1998) argue that investor overconfidence and self-attribution bias can lead to market under- and overreactions.

ability improves with experience. They conclude (p. 733) "an open question in the literature is why there is such high trading volume, particularly among seemingly uninformed individual investors. Our results indicate that such trading may be rational; investors may be aware that they will learn from experience and trade in order to learn." While these papers do not dismiss behavioral motives for trade, they make a strong case that learning could explain much of observed trading behavior.

But does it? For tens of thousands of Taiwanese day traders the answer is clearly "no." In expectation the lifetime profits from day trading are negative. Though profitable traders stay in the market longer than unprofitable traders, the unconditional likelihood of becoming predictably profitable is so low that a risk adverse investor would not undertake day trading in hopes of becoming one of the few. Of course, a few investors with unusual abilities such as extraordinary mathematical skills, might rationally anticipate becoming successful day traders. But each unusual investor with a positive ex-ante expectation of profitable day trading reduces the expected day trading returns of the ordinary investors. Furthermore, experienced day traders with a history of net losses persist in trading at nearly the same rate as those with a history of gains. Given the overwhelming lack of profitability of day traders and the persistence of trading in the face of losses, rational trading to learn cannot account for "high trading volume … among seemingly uninformed individual investors." If these traders are trading to learn, they are learning slowly.

I. Learning by Speculators

The suggestion that investors learn from experience is neither novel nor controversial.[3] 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.

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[3] 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).

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. However, in equilibrium, for the expected life-time profits of prospective speculators to positive, aggregate profits earned by speculators must be profitable. 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. In steady state (after 10 years), aggregate speculator profits each year are -$10, with 20 new and unskilled traders who lose $1 and 10 skilled traders who make $1. 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 unconditional expected lifetime profits of a speculator. Furthermore, since skilled speculators stay in the market longer than unskilled, in equilibrium the proportion of traders in the market at any time who have skill is greater than the unconditional probability that a new trader has skill. (E.g., $10/30^{th}$ vs $1/21^{st}$ in our example). 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 net performance of day traders is positive (non-negative).

The alternative is that the aggregate net 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, 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 Bayesian 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, nearly 3/4ths of day-trading volume is generated by unsuccessful day-traders with at least 10 days of day trading experience and, in an average month, only 9% of those day traders who have 400 or more days of day trading experience have earned positive lifetime intraday net returns. This perverse persistence might results from biased prior beliefs, biased learning, or both.

The rational learning models predict that unsuccessful speculators will quit while successful speculators are likely to persist. Thus—irrespective of prior beliefs—the rational learning models predict our second null hypothesis:

H2: Experienced day traders with previous net losses will stop trading speculatively.

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 continuing to trade by experienced 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 investor 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 larger and the time-series much longer than those in prior studies.[4] The one exception to this generalization being Barber, Lee, Liu, and Odean (2014) who identify a small subset of day traders (less than 1% of the day trading population) predictably earn 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.[5] Minimum tick sizes are set by the TSE and vary depending on the price of the security. Generally, orders are cleared using automatching

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[4] 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.

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

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%.

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).[6] 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

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[6] 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.

Services held over \$NT 213 billion in Taiwanese stock).[7] 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 $(\frac{1}{2}*P_b*min(S_b,S_s)+\frac{1}{2}*P_s*min(S_b,S_s))$. Over our sample period, aggregate day trading accounts for more than 19% of the total dollar value of aggregate trading volume.

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.

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[7] 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.

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, the share of volume traced to day trading has been consistently around 20% of total trading volume from 1995 to 2006. In the average month, almost 140,000 individuals day trade[8]. 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 primary performance measurement focuses on the intraday profits of all trades made by day traders and on trade-weighted intraday returns. In a subsequent analysis, we also analyze the event time profitability of purchases and sales to ensure the inferences we draw from the analysis of intraday profits are accurate.

We calculate the intraday returns to day trading, by identifying all trades made by day traders. We calculate the profits on round-trip day trades and other position opening 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 intraday return from day trading. To calculate the net intraday return to day trading, we assume a 5 basis points (bps) commission on purchases, a 5 bps commission on sales, a 30 bps transaction tax on sales. (See appendix for details.)

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[8] Most of the 140,000 individuals who day trade in a month do not do so for all months of the year. Analyzing these same data, Barber, Lee, Liu, and Odean (2014) estimate that approximately 450,000 individuals day trade in a typical year.

We calculate a trader's past intraday returns to see whether quitting is sensitive to past performance. When calculating these returns we do not market adjust. We believe that when evaluating their past performance day traders are unlikely to market adjust because of their short holding periods and the low market betas of their portfolios. When evaluating future performance we do adjust for market returns because an obvious alternative to day trading would be to hold the market portfolio. Market adjusting does not qualitatively change our findings.

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

III. Rational and Behavioral Learning Models: Confirming Evidence

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 2, we present a five-year Kaplan-Meier survival function. We consider the survival of day traders who have day traded for at least 10 days and designate the first month when they hit the minimum 10-day threshold as their entry month. For many of

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

these traders, day trading is a persistent activity. Only 2.5% drop out within one month, while survival rates at one, two, and three years are 44%, 24% and 15% respectively.

To test whether magnitude of past profitability affects the decision to quit day trading, we estimate the following Cox proportional hazard rate model,

$$h(t,x) = h_0(t)e^{\{XB\}}, \tag{1}$$

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.

Again, we restrict our analysis to day traders who have day traded for a minimum of 10 days. To assess the impact of past performance on quitting, we use net intraday returns. To estimate the impact of past returns on the propensity to quit day trading, we construct a series of 26 dummy variables corresponding to the following ranges in basis points of performance net of trading costs: (-∞, -90], (-90, -85], … , (25, 30], (30, ∞). When estimating the Cox proportional hazard rate model, we set the range (0, 5 bps] as the default category and include the remaining 25 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, the log of the number of days since a trader's first day trade, and the log of the total volume of day trading. In the event history analysis, all independent variables are updated monthly.

The results of this analysis are presented in Figure 3. The horizontal axis of the figure represents net intraday return categories, while the vertical axis represents the hazard rate relative to the omitted profit category (net intraday return in the interval (0, 0.05]). As predicted by the learning models, the net intraday return is negatively related to the hazard rate. More profitable day traders are less likely to quit.[10]

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[10] 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. Traders with more days of day trading experience are less likely to quit; a one standard deviation increase in the log of number of days of past day trading reduces the base case hazard rate to 0.43. Day traders who have been trading longer are more likely to quit; a one standard deviation in the log of the number of days since a trader's first day trade increases the hazard rate to 1.24. Heavy day traders are more likely to quit; a one standard deviation increase in the log of past day trading volume increases the hazard rate to 1.11.

However, the effect is not linear. The propensity to quit is relatively insensitive to differences past net intraday returns in the -30 bps to 30 bps range. Traders with past net intraday returns in the (30 bps, infinity) range are more likely to quit than those with returns in the -30 bps to 30 bps range, though not as likely as traders with more negative returns.

In the domain of negative returns, the propensity to quit is quite sensitive to the magnitudes. For example, consider the impact on hazard rates of moving across four equidistant profit categories: (0, 0,05], (-0.30, -0.25], (-0.60, -0.55] and (-0.90, -0.85]. The first move, from just profitable to the low range of losses increases the hazard rate six percentage points (from 1.00 to 1.06); the second move, from the low range of losses to mid range losses, increases the hazard rate by an additional 30 percentage points (from 1.06 to 1.36), the third move, from the mid range of losses to a high range increases the hazard rate by an additional 36 percentage points (from 1.36 to 1.72).

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.

IV. Rational Learning Models: Disconfirming Evidence

To this point, we find support for the rational and behavioral learning models of investor behavior. Poor performers are more likely to quit day trading. 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.

A. 1. Aggregate performance is negative

To evaluate the performance of day traders relative to their opportunity cost of holding the market portfolio, 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 (market return less the risk-free rate). 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.

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

There are two reasons that including all trades in the month of day trading might positively bias our performance analysis. First, 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). (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 abnormal intraday returns of day traders. On average, day traders lose 7 basis points on their day trading before costs (t=-10.2). In the fourth column we see that trading costs more than triple the losses to 23.9 basis points per day. Moreover, we observe reliably negative gross and net performance in all years but 1992, when gross returns are indistinguishable from zero but net returns are reliably 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.

A. 2. Experienced Day Traders Continue To Lose Money

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

Do traders with a long history of losses continue to trade? To investigate the relation between experience, past performance, and continued trading we categorize day traders into groups based upon past day trading experience and whether or not they have been profitable. Each month from 1993-2005, we sort traders based on the number of days they have engaged in day trading and on the cumulative profitability of their past intraday trades as of the end of the previous month. To have an accurate measure of day trading experience, we exclude traders who day traded in 1992. We exclude traders with fewer than 10 days of past day trading experience and sort the remaining traders into those with 10 to 49 days, 50 to 99 days, 100 to 199 days, 200 to 399 days, and 400 or more days of day trading experience. We further partition these experience groups into those with positive cumulative past intraday profits and those with negative or zero cumulative past intraday profits. We then measure the propensity for traders in each experience/profitability group to stop day trading for one month or for twelve consecutive months.

Table 2 Panel A reports the rate at which traders stop day trading for at least one month. Not surprisingly, traders with less experience are more likely to stop. For example, 41.98% of profitable traders and 43.19% unprofitable traders with 10 to 49 days of experience stop trading for at least one month while only 7.58% of profitable traders and 9.30% of unprofitable traders with 400 or more days of experience do so. As predicted by both rational and behavioral learning models, unprofitable traders are more likely to stop trading than profitable traders. Across the five experience bins, the unprofitable traders quit at rates ranging from 1.21 to 2.73 percentage points higher than profitable traders. What is more surprising is that the magnitude of the differences in the quitting rates of profitable and unprofitable traders, though statistically significant, is tiny.

Table 2 Panel B reports the rates at which traders stop day trading for at least twelve consecutive months. Naturally, these rates are lower than those for stopping for a month, but a similar pattern emerges as in Panel A. For example, 5.43% of profitable traders and 6.55% of unprofitable traders with 10 to 49 days of experience stop trading for at least twelve months. Of traders who have day traded 400 or more days, profitable traders have a 1.58% probability of quitting for twelve or more months and unprofitable traders have a 2.05% probability quitting. Using columns 2 – 5 and the last four rows of Panel B one can calculate that all previously unprofitable traders with 50 or more days of past day trading experience have a 95.3% probability of day trading again in the next 12 months, while previously profitable traders with similar experience have a 96.4% probability doing so. Traders are sensitive to losses, but not very sensitive.

What fraction of day trading can we trace to traders with a history of losses? To answer this question, each month we sort traders who day trade that month into three groups: novice day traders (traders with 1 to 9 days of day trading experience), unprofitable day traders (traders with 10 or more days of day trading experience and negative or zero life time net intraday profits prior to the month of sorting), and profitable day traders (traders with 10 or more days of day trading experience and positive life time net intraday profits prior to the month of sorting). In Figure 4 we graph the relative sizes of these three groups from 1995 through 2006 when measured by number of traders (Figure 4a) and trading volume in dollars (Figure 4b). Throughout this twelve-year period the fraction of profitable day traders is consistently about 5%. The fraction of unprofitable traders grows to over 2/3rds as more and more novice day traders are reclassified as profitable or unprofitable. As one would expect, profitable and unprofitable day traders account for proportionately more trading volume than novice day traders. In aggregate over the sample period, unprofitable traders account for 72% of trading volume and in the last several years of the sample they consistently account for about 80% of trading volume.

Thus, most day traders are unprofitable, previously unprofitable traders generate most day trading, and previously unprofitable day traders with considerable experience persist at day trading at almost the same high rate as profitable experienced day traders. These observations are not consistent with models of rational learning.

We sort day trader based on past profitability and experience. A reasonable concern is that if these sorts are not good indicators of future performance, traders might reasonably ignore them. However as we demonstrate in the next section, sorting day traders on experience and past profitability is remarkably effective at forecasting their future performance.

A. 3. Event Time Analysis and the Persistence of Performance

So far we considered only intraday returns. This is appropriate given our focus on day trading. However, not all positions initiated by day traders are closed the day they are opened. Do day traders earn profits on positions that they hold beyond the close of trading? We address this question with an event time analysis of returns subsequent to purchases and sales.

Each day we sort traders on profitability and experience over the last 365 calendar days (366 for leap years). Profitable traders earn a cumulative intraday net profit over the previous year that are positive, and unprofitable traders earn negative or zero profits. Experience bins are based on number of days of day trading during the previous 365 days with: Low experience (0-5 days), Exp. 2 (6-10), Exp. 3 (11-20), Exp. 4 (21-40), Exp. 5 (41-80), Hi Exp. (> 80). We aggregate all purchases by day traders in each group by stock and day where the day of the transaction is event day 1. We then calculate the mean market-adjusted abnormal return on event day τ (MA$_\tau$) (weighted by the value of stocks bought) using purchase prices and closing prices to calculate event day 1 market adjusted returns and ignoring trading costs. There is a similar calculation for the sales of each group. Finally, we calculate the cumulative (market-adjusted) abnormal return on stocks bought less the cumulative (market-adjusted) abnormal return on stocks sold as:

$$CAR_T = \sum_{\tau=1}^{T}(MA_\tau^{buy} - MA_\tau^{sell}).$$

(2)

The results for a 10 trading day event horizon are displayed in Figure 5. The most striking results in the graph are: 1) irrespective of experience, traders with past profits outperform those with past losses and 2) for traders with positive past profits, cumulative abnormal returns increase with experience, and 3) profitable traders with more than 40 days of day trading experience in the last year earn more than enough to cover 40 basis

points of round trip transaction costs. Most of this profit is earned on the day of the transaction.

We look at the persistence of profitability from another angle by calculating, as in Table 1, gross and net abnormal intraday returns. We partition day traders daily using the same criteria as for Figure 5. Results are reported in Table 3. 1) Irrespective of experience, traders with past profits outperform those with past losses, 2) for traders with positive past profits, cumulative abnormal returns increase with experience, and 3) profitable traders with more than 40 days of day trading experience in the last year earn more than enough to cover their transaction costs.

These results confirm that an extensive history of profitability is a strong predictor of future profitable. However, very few traders are predictably profitable. In the last column of Table 3, we see that only 9.81% (3.20%+6.61%) of day trading volume is generated by predictably profitable day traders. From column 8, we can calculate that these predictably profitable traders constitute less than 3% of all day traders active on an average day.[11]

V.   Discussion

Our data are remarkably well suited for testing models of rational learning such as Mahani and Bernhard (2007). 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 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

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[11] Because highly experienced profitable day traders trade more actively than others, they are overrepresented when measured on a daily basis. Employing different methodology, Barber, Lee, Liu, and Odean (2014) estimate that less than 1% of individuals who day trade over the course of a year are predictably profitable.

aggregate, lose money. 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, 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.[12] Some investors may choose to day trade in hopes of impressing others.[13]

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.

VI. Conclusion

We test predictions of models of learning by rational traders and find clear evidence that the decision to continue day trading is influenced by previous day trading

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[12] 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 (2009) 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.

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

returns. Nevertheless, rational models of learning do not explain all or even most day trading. Only the most experienced previously profitable day traders—less than 3% of active day traders on an average day--earn predictably positive net returns, and yet most experienced unprofitable day traders continue to trade and continue to reap losses. Nearly 3/4ths of 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 trading when ex-ante expected lifetime profits are negative. For prospective day traders, "trading to learn" is slow learning.

References

Barber, Brad M., Chip Heath, and Terrance Odean, 2003, Good Rationales Sell: Reason-Based Choice Among Group and Individual Investors in the Stock Market, *Management Science*, 49, 1636-1652.

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2007, Is the Aggregate Investor Reluctant to Realize Losses? Evidence from Taiwan, European Financial Management, 2007, Vol. 13, 423-447.

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2009, Just How Much Do Individual Investors Lose by Trading?, *Review of Financial Studies*, 22, 609-632.

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2014, The Cross-Section of Speculator Skill: Evidence from Day Trading, *Journal of Financial* Markets, 18, 1-24.

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

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

Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, Do Retail Trades Move Markets? *Review of Financial Studies*, 22, 151-186.

Biais, Bruno, Denis Hilton, Karine Mazurier, and Sébastien Pouget. "Judgemental overconfidence, self-monitoring, and trading performance in an experimental financial market." *The Review of Economic Studies* 72, no. 2 (2005): 287-312.

Boehmer, Ekkehart and Jones, Charles M. and Zhang, Xiaoyan, 2017, Tracking Retail Investor Activity. Available at SSRN: https://ssrn.com/abstract=2822105

Caballé, Jordi, and József Sákovics. "Speculating against an overconfident market." *Journal of Financial Markets* 6, no. 2 (2003): 199-225.

Campbell, John Y. and Ramadorai, Tarun and Ranish, Benjamin, Getting Better or Feeling Better? How Equity Investors Respond to Investment Experience, 2014. Available at SSRN: https://ssrn.com/abstract=2413348

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

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. "Investor psychology and security market under-and overreactions." *the Journal of Finance* 53, no. 6 (1998): 1839-1885.

Deaves, Richard, Erik Lüders, and Guo Ying Luo. "An experimental test of the impact of overconfidence and gender on trading activity." *Review of finance* 13, no. 3 (2008): 555-575.

De, Sankar , Gondhi, Naveen R. and Pochiraju, Bhimasankaram, 2010, Does Sign Matter More than Size? An Investigation into the Source of Investor Overconfidence. Available at SSRN: http://ssrn.com/abstract=1657926.

Dorn, Anne Jones, Daniel Dorn, and Paul Sengmueller. "Trading as gambling." *Management Science* 61, no. 10 (2014): 2376-2393.

Dorn, Daniel, and Paul Sengmueller. "Trading as entertainment." *Management Science* 55, no. 4 (2009): 591-603.

Gao, Xiaohui, and Tse-Chun Lin. "Do individual investors treat trading as a fun and exciting gambling activity? Evidence from repeated natural experiments." *Review of Financial Studies* 28, no. 7 (2014): 2128-2166.

Garvey, Ryan, and Anthony Murphy, 2002, How Profitable Day Traders Trade: An Examination of Trading Profits, working paper, University College Dublin, Dublin, Ireland.

Garvey, Ryan and Anthony Murphy, 2005, The Profitability of Active Stock Traders, *Journal of Applied Finance*, 93-100.

Gervais, Simon, and Terrance Odean, 2001, Learning to be Overconfident, *Review of Financial Studies*, 14, 1-27.

Glaser, Markus, and Martin Weber. "Overconfidence and trading volume." *The Geneva Risk and Insurance Review* 32, no. 1 (2007): 1-36.

Grinblatt, Mark, and Matti Keloharju, 2000, The Investment Behavior and Performance of Various Investor Types: A Study of Finland's Unique Data Set, *Journal of Financial Economics*, 55, 43-67.

Grinblatt, Mark, and Matti Keloharju, 2001, What makes investors trade?, *Journal of Finance*, 56, 589-616.

Grinblatt, Mark, and Matti Keloharju, 2009, Sensation Seeking, Overconfidence, and Trading Activity, *Journal of Finance*, 64, 549-578.

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

Hong, Harrison, and Marcin Kacperczyk, 2009, The Price of Sin: The Effects of Social Norms on Markets, *Journal of Financial Economics,* 93, 15-36.

Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2008, Individual investor trading and stock returns. *Journal of Finance*, 63, 273–310.

Kelley, Eric, and Paul Tetlock, 2013, How Wise Are Crowds? Insights from Retail Orders and Stock Returns, *Journal of Finance*, 68, 1229-1265.

Kumar, Alok, 2009, Who Gambles in the Stock Market, *Journal of Finance*, 64, 1889-1933.

Linnainmaa, Juhani T., 2003, The Anatomy of Day Traders. AFA 2004 San Diego Meetings. Available at SSRN: http://ssrn.com/abstract=472182 or doi:10.2139/ssrn.472182

Linnainmaa, Juhani T., 2005, The Individual Day Trader, 2005, UCLA working paper.

Linnainmaa, Juhani T., 2011, Why Do (Some) Households Trade So Much?, *The Review of Financial Studies*, 24, 1630-1666.

Lubensky, Dmitry, Learning from Speculating and the No Trade Theorem (January 6, 2017). Available at SSRN: https://ssrn.com/abstract=2049580.

Mahani and Bernhardt, 2007, Financial Speculators' Underperformance: Learning, Self-Selection, and Endogenous Liquidity, *Journal of Finance*, 62, 1313-1340.

Nicolosi, Gina, Peng, Liang, and Ning Zhu, 2009, Do Individual Investors Learn from Their Trading Experience?, *Journal of Financial Markets*, 12, 317-336.

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

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

Seasholes, Mark and Guojun Wu, 2007, Predictable Behavior, Profits, and Attention, *Journal of Empirical Finance*, 14, 590-610.

Seru, Amit, Shumway, Tyler, and Noah Stoffman, 2010, Learning by Trading, *Review of Financial Studies*, 23, 705-739.

Statman, Meir, 2004, What Do Investors Want?, *Journal of Portfolio Management*, 153-161.

APPENDIX: Details of Return and Profit 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:

$$r_{gt} = \frac{\sum_i \sum_j \left(S_{ijt}^L - B_{ijt}^L\right) + \left(S_{ijt}^S - B_{ijt}^S\right)}{\sum_i \sum_j \left(B_{ijt}^L + S_{ijt}^S\right)},$$

(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 value $\left(S_{ijt}^L\right)$ is the value based on 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 value $\left(B_{ijt}^S\right)$ is the value based on the actual transaction price or the closing price if the short position is not closed out prior to the end of trading. The numerator in equation A1 is the intraday gross profit of trader i on day t.

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 and net profits, 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:

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

(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 40 bps because we also increase the capital required to open the positions. The numerator in equation A2 is the intraday net profit of trader i on day t.

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

This table presents the daily percentage alpha from aggregate day trading of day traders. Day trading is defined as round-trip trades by the same stock/investor/day. Each day all investor's trades are included in this analysis if the trader made at least one day trade in the calendar month. The alphas are estimated using the following calendar time regression of daily returns: $(Rpt-Rft)=\alpha_p+\beta_p(Rmt-Rft)+\varepsilon_{pt}$, where Rpt, Rmt, and Rft are the portfolio return, market return, and risk-free 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.

	Gross		Net			
	α(%)	t-stat	α(%)	t-stat	Beta	R-Sq
All Years	-0.070	-10.20	-0.239	-34.78	0.26	43%
1992	0.018	0.57	-0.091	-2.91	0.37	49%
1993	-0.089	-3.40	-0.206	-7.80	0.33	59%
1994	-0.119	-5.03	-0.275	-11.65	0.32	58%
1995	-0.047	-2.18	-0.221	-10.23	0.24	45%
1996	-0.088	-4.90	-0.245	-13.58	0.26	48%
1997	-0.089	-3.27	-0.271	-10.00	0.26	39%
1998	-0.067	-3.13	-0.256	-11.99	0.21	43%
1999	-0.053	-1.91	-0.224	-8.04	0.25	42%
2000	-0.007	-0.18	-0.190	-5.23	0.23	36%
2001	-0.088	-2.43	-0.279	-7.68	0.24	37%
2002	-0.104	-3.47	-0.289	-9.67	0.23	39%
2003	-0.100	-4.39	-0.280	-12.34	0.22	38%
2004	-0.062	-2.51	-0.244	-9.90	0.22	39%
2005	-0.087	-5.00	-0.280	-16.23	0.28	41%
2006	-0.089	-4.07	-0.277	-12.82	0.26	38%

Table 2. Quitting Day Trading Conditional on Experience and Past Profitability

Day trading is defined as round-trip trades by the same stock/investor/day. In panel A, we present the percentage of traders who day trade in month t-1 but not in month t. In Panel B, we present percentage of traders who day trade in month t-1 but not in months t through t+11 We sort traders on experience (rows) and profitability (columns). Experience is the number of previous days on which a trader has day traded through month t-1. Only traders with 10 or more days of day trading experience are included. Profitable day traders are those with mean daily intra-day returns that are positive through month t-1. The analyses begin in 1993 and exclude traders who day traded in 1992. N is the number of trader/month observations.

Experience (X) Partition	Unprofitable Traders		Profitable Traders		Difference in Means	*t*-statistic (difference in means)
	Mean	N	Mean	N		
Panel A. Percentage of Day Traders who Day Trade in Month t-1 but do not Day Trade in Month t						
10 d <= X < 50 d	43.19%	5,578,277	41.98%	540,228	1.21%	17.19
50 d <= X < 100 d	29.82%	2,460,476	27.08%	154,435	2.73%	23.41
100 d <= X < 200 d	22.47%	2,018,002	20.06%	123,009	2.41%	20.45
200 d <= X < 400 d	15.95%	1,344,396	13.67%	90,711	2.28%	19.27
400 d <= X	9.30%	832,988	7.58%	81,713	1.72%	17.54
Panel B. Percentage of Day Traders who Day Trade in Month t-1 but not in Months t to t+11						
10 d <= X < 50 d	11.73%	5,578,277	11.41%	540,228	0.33%	7.18
50 d <= X < 100 d	6.55%	2,460,476	5.43%	154,435	1.12%	18.73
100 d <= X < 200 d	4.62%	2,018,002	3.65%	123,009	0.98%	17.61
200 d <= X < 400 d	3.24%	1,344,396	2.43%	90,711	0.81%	15.18
400 d <= X	2.05%	832,988	1.58%	81,713	0.47%	10.20

Table 3. The Calendar Time Performance of Day Traders conditional on Prior Year's Day Trading Experience and Profitability

Day Traders are grouped based upon how many days they engaged in day trading and whether their intraday returns were profitbale during the previous 365 days. The alphas are estimated using the following calendar time regression of intraday 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. "Day Trade / All Trade" is the fraction of the group's trading that is round-trip day trades. The last column presents the share of all day trading accounted for by each group.

| # Days of Day Trading Experience in Previous Year	Gross		Net					Day Trades / All	Share of All Day Trading by
	α(%)	t-stat	α(%)	t-stat	Beta	R-Sq	Average Daily N	Trades	Volume
Panel A. Previously Profitable Day Traders									
0 d <= X < 5 d	-0.066	-7.64	-0.140	-16.26	0.33	46%	14936	9.73%	7.81%
6 d <= X < 10 d	0.001	0.18	-0.107	-14.57	0.29	46%	2110	18.90%	2.12%
11 d <= X < 20 d	0.053	7.75	-0.070	-10.32	0.27	47%	1976	22.53%	2.50%
21 d <= X < 40 d	0.120	19.33	-0.019	-3.14	0.24	47%	1732	26.34%	2.90%
41 d <= X < 80 d	0.197	35.39	0.035	6.34	0.21	46%	1455	33.36%	3.20%
80 d <= X	0.333	72.65	0.118	26.03	0.17	45%	1724	50.52%	6.61%
Panel B. Previously Unprofitable Day Traders									
0 d <= X < 5 d	-0.139	-16.10	-0.213	-24.60	0.33	46%	46078	8.95%	20.55%
6 d <= X < 10 d	-0.167	-20.75	-0.270	-33.60	0.31	47%	9468	18.52%	6.81%
11 d <= X < 20 d	-0.171	-21.98	-0.289	-37.26	0.31	47%	10335	23.99%	8.77%
21 d <= X < 40 d	-0.171	-23.05	-0.310	-41.83	0.30	48%	10308	30.47%	10.47%
41 d <= X < 80 d	-0.166	-23.71	-0.332	-47.56	0.28	49%	9184	37.81%	11.34%
80 d <= X	-0.132	-21.88	-0.348	-57.90	0.25	50%	9639	50.72%	16.91%
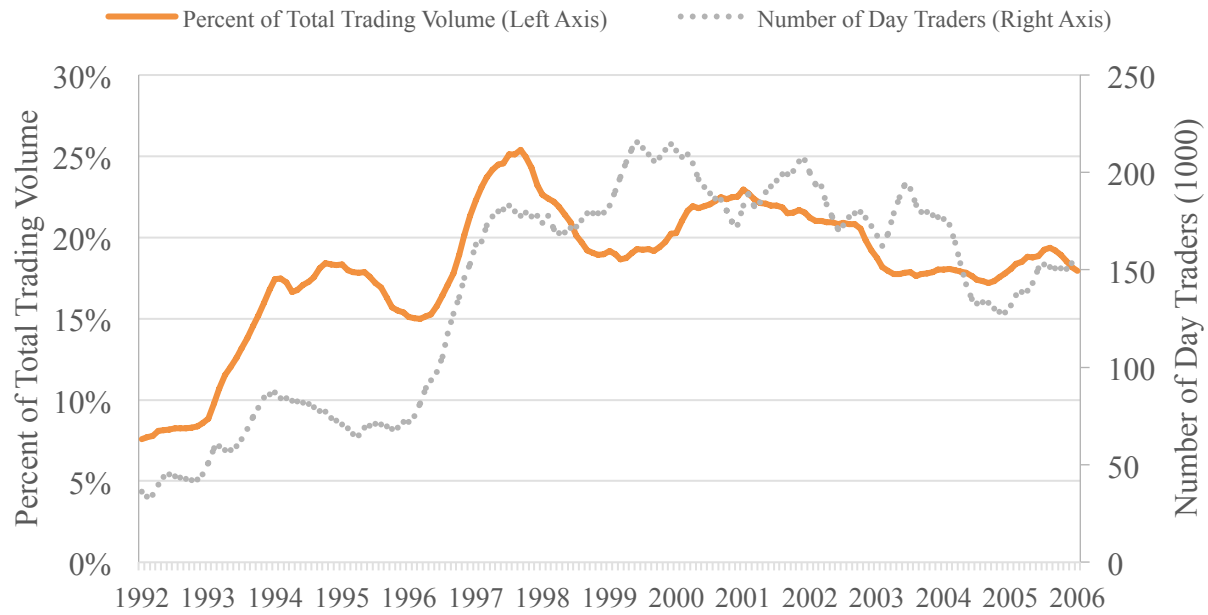
Figure 1. Day Trading as a Percent of Total Volume and Number of Individual Day Traders
The figure presents the 12-month moving average for (1) the number of individual investors who engage in day trading and (2) day trading as a percent of total trading volume.
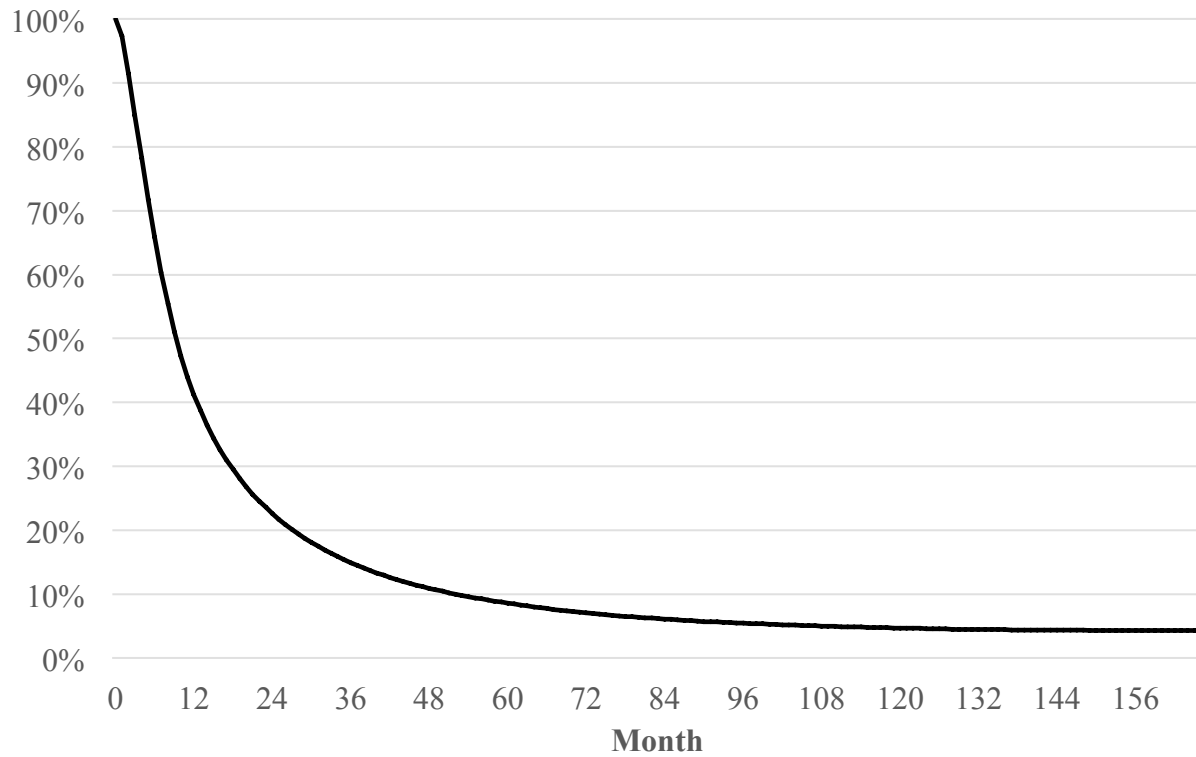
Figure 2. Day Trader Survival Function

Observations are monthly. Entry in month 0 is defined as the month when a day trader has 10 or more days of day trading. Quitting (the failure event) is defined as the first month in which we observe no day trading in 12 consecutive months.
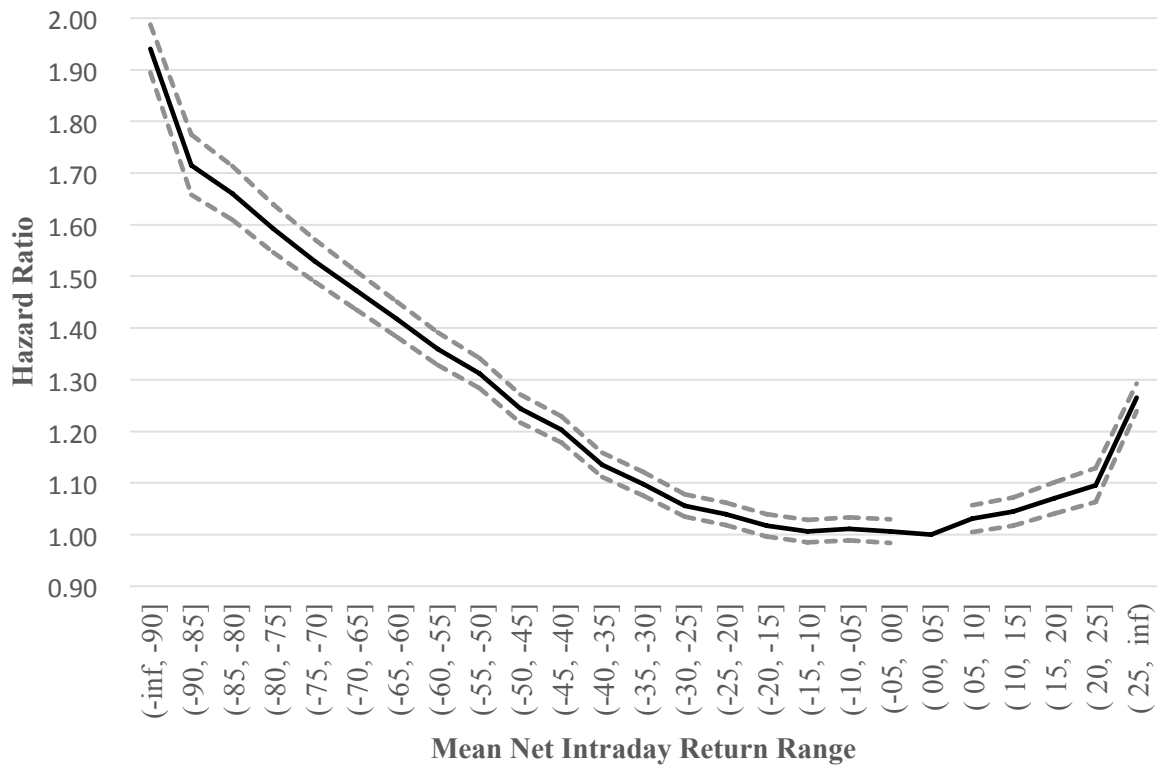
Figure 3. Hazard Ratio for Quitting Day Trading Conditional on Past Performance, 1993-2005.
Observations are monthly and exclude traders who day traded in 1992 or started in 2006. Entry in month 0 is defined as the month when a day trader has 10 or more days of day trading. Quitting (the failure event) is defined as the first month in which we observe no day trading in 12 consecutive months. The figure reports the hazard ratio for quitting (solid line) and the 95% confidence interval (dashed lines) for different return categoreis relative to the default category of (0,5] basis points (bps) where the hazard ratio is equal to one by construction. Mean net intraday return range is the investor's average daily return on days with trades from the first month of day trading to the end of the prior month.
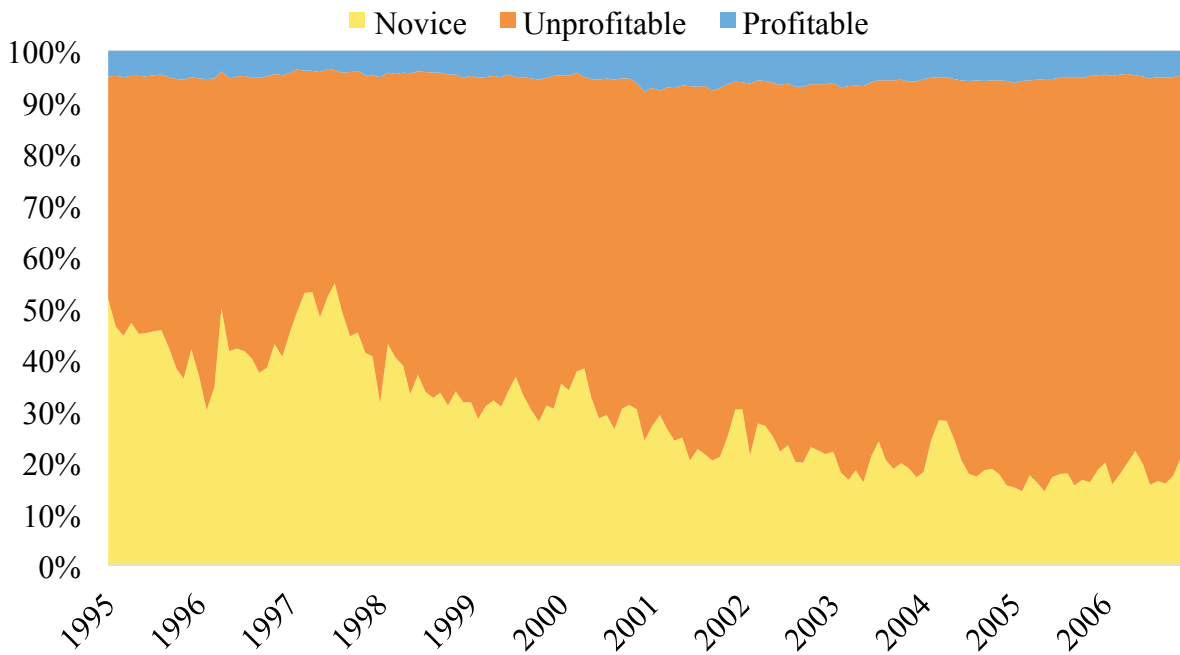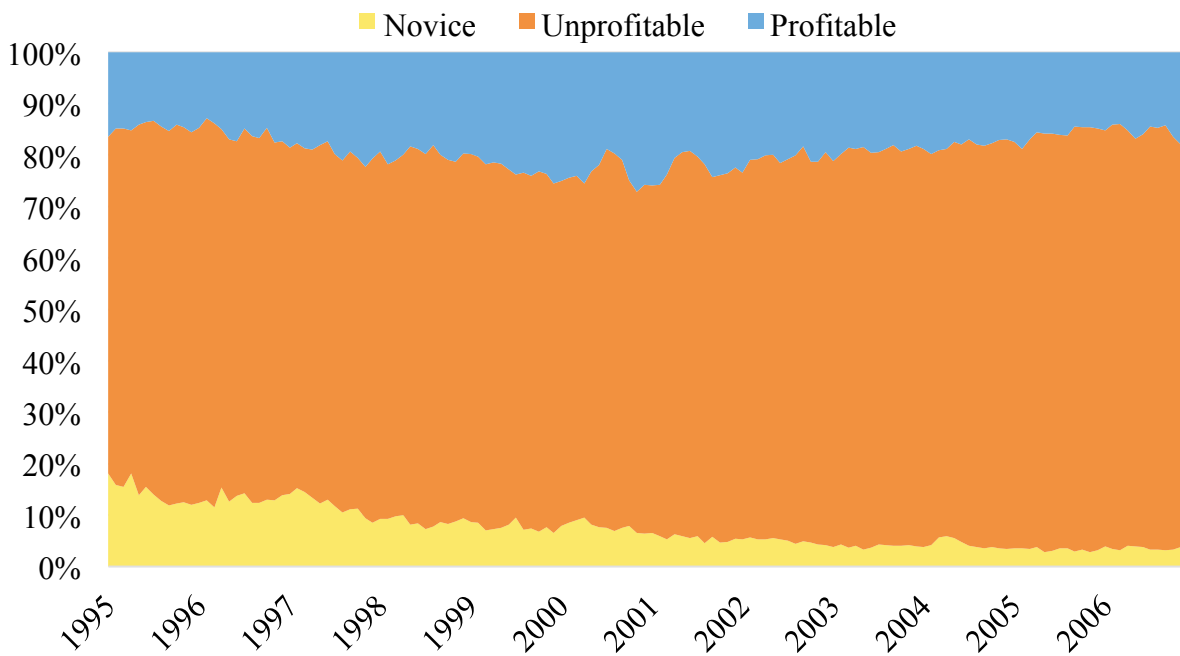
Figure 4. Day Trading by Novice, Profitable, and Unprofitable Day Traders
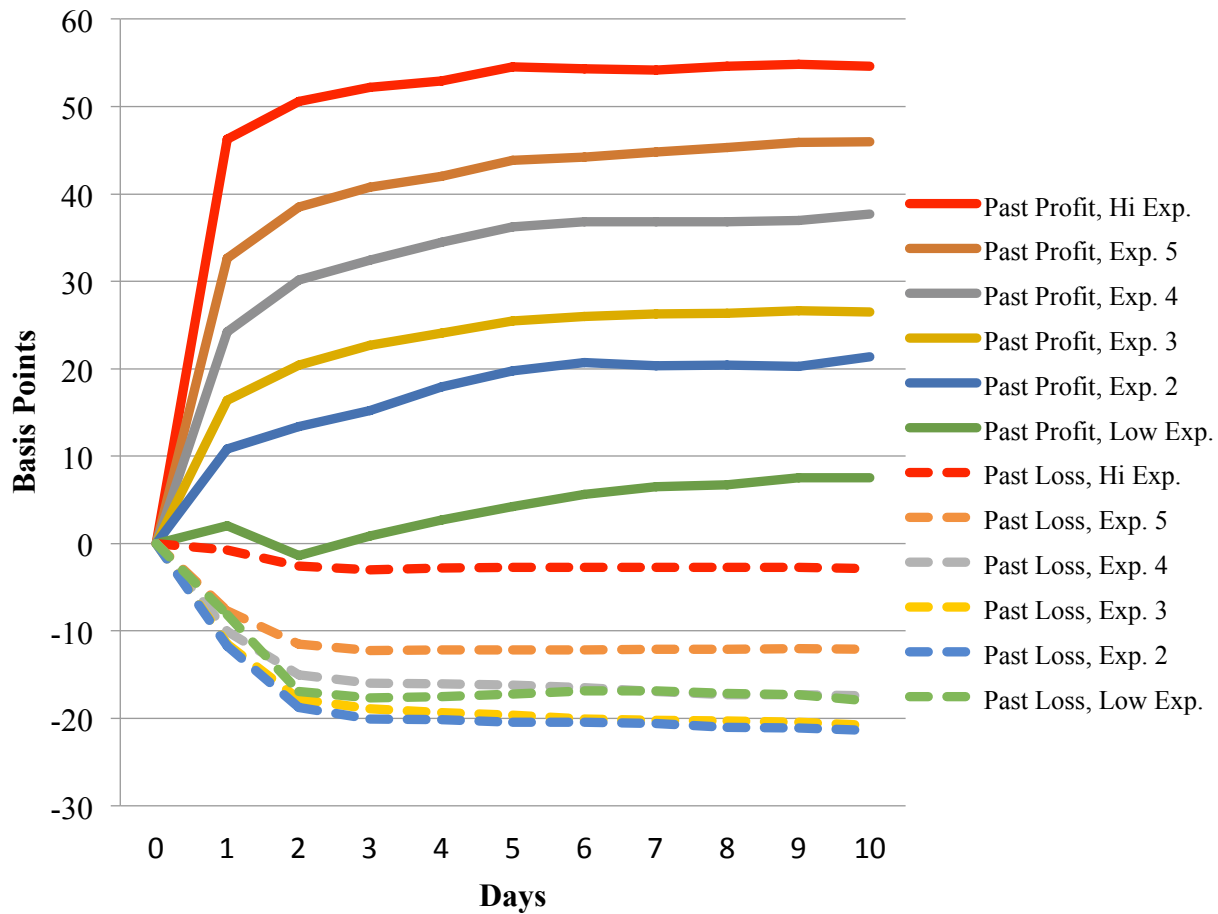Novice day traders are those with less than 10 days of day trading.

Figure 5. Cumulative abnormal returns (CARs) in Event Time conditional on Past Profitability and Experience, 1993-2005

On event day 1, traders who day trade that day are sorted based on net profitability of intraday trades and day trading experience over previous year. Profitable (unprofitable) traders are those with cumulative intraday net profits over the previous 365 calendar days that are positive (negative or zero). Experience bins are based on number of days of day trading during the previous 365 days with: Low experience (0-5), Exp. 2 (6-10), Exp 3 (11-20), Exp 4 (21-40), Exp 5 (41-80), Hi Exp (> 80).