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What do individual traders of TAIEX futures learn from their trading activities?
是否台指期貨交易者能從交易中學習?

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Abstract: This study analyzes what individual traders who engage in TAIEX futures learn from their trading with data covering all TAEIX futures contracts between January 2004 and December 2008. We use a semi-parametric regression model and a Cox proportional hazard rate model for data analysis and find that losing traders stop trading actively after realizing their poor ability of trading, thus supporting the rational learning model. However, traders' performance does not improve until they have enough trading experience. This finding indicates that traders have limited rationality and that the speed of learning from trading is irritatingly slow.

Keywords: Experience, Learning, Performance

1. Introduction

Academics have recently paid a great deal of attention to whether individuals can learn from their mistakes and over time develop a good sense of knowledge. Theoretically, Mahani and Bernhardt (2007) and Linnainmaa (2011) propose a rational learning model in which traders initially do not know their own abilities and must infer them by observing their trading performance. They use the information from their trading profits to understand whether or not they have the ability to reliably profit from trading. Those who lose money from

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trading are likely to be inept traders and leave the market. In contrast, those who earn sufficient profits regard themselves as skilled traders and expand their trading activities. Thus, if people are rational and measure their success and failure equally, then experience should engender wisdom and performance should improve over time.

Various studies indeed offer empirical evidence that traders can learn from their trading experience by testing rational learning models, using stock trades as their focus (e.g., Feng and Seasholes, 2005; Nicolosi, Peng, and Zhu, 2009; Seru, Shumway, and Stoffman, 2009). However, a growing stream in the literature on behavioral economics and finance has provided strong evidence that individuals are not fully rational and do not become more rational over time (e.g., Gervais and Odean, 2001; Barberis and Thaler, 2002). For example, confirmation bias - the tendency to search out evidence consistent with prior beliefs and to ignore conflicting data - contributes to limited rationality. Moreover, self-attribution bias leads people to remember their successes with great clarity. Gervais and Odean (2001) present a multi-period model that indicates past successes contribute to traders becoming overconfident due to the self-attribution bias. Specifically, although traders realize their ability through trading, when they are successful, these traders irrationally attribute success disproportionately to their ability rather than luck. This irrationality leads them to overestimate their own abilities and trade too aggressively. The model of Gervais and Odean (2001) also predicts that a trader's level of overconfidence first increases over his or her first several trading periods and then declines as his or her trader's life progresses.

In this study we obtain a unique account-level dataset from the Taiwan Futures Exchange (TAIFEX), enabling us to examine each individual's trading behavior and performance on futures of Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and to determine whether individual traders are rational or behavioral learners.[2] Glaser and Weber (2007) argue that individuals

[2] Prior studies on TAIEX futures usually employ futures trading data to examine whether this futures market conveys more information than the spot market (Chan *et al.*, 2007), the pricing model of stock index futures (Wang and Chueh, 2006), the effect of a transaction tax on the relation between volatility and trading activities (Chen *et al.*, 2010), the effect of herding behavior and investors' sentiments on TAIEX futures (Chang *et al.*, 2015), and the price discovery of TAIEX futures (Wang *et al.*, 2014).

cannot correctly assess their own realized stock portfolio performance,[3] which hinders their learning. However, they also find that the daily marking-to-market feature of a futures contract compels futures traders to correctly evaluate their performance. This feature makes the trading of futures a better and instinctive reflection of traders' profit motives and offers a clearer view of their behavioral biases. The empirical works on learning in financial markets usually use data from equity markets (Barber *et al*., 2011; Chiang *et al*., 2011; Linnainmaa, 2011; Seru, Shumway, and Stoffman, 2010). Although there is evidence that individual traders in equity markets can learn from experience, it is unclear whether traders in futures markets have the same learning behavior. The contribution of this study is to fill this gap in the literature.

Seru, Shumway, and Stoffman (2009) posit that there are two types of learning: traders can either learn to become better at trading (learning-by-doing) or learn to quit trading after realizing their inferior ability (learn-about-ability). To the extent that prior studies usually focus on the first type, we separate these types of learning empirically and examine which type of learning occurs more frequently. The learning-by-doing model depends on whether traders improve their performance over time through trading. Therefore, we use a semi-parametric regression to analyze the relation between experience and return and follow Brown and Goetzmann (1995) and Brown, Goetzmann, and Ibbotson (1999) to examine whether performance is persistent. If returns increase with experience and profitable traders have persistent performance, then this evidence supports the learning-by-doing hypothesis. By contrast, the learn-about-ability model relies on whether traders cease trading after repetitive losses. Thus, we calculate the accumulated numbers of orders placed and days in the market before leaving the market and then run a Cox proportional hazard rate model to examine whether unprofitable traders stop trading quickly.

The empirical results show that the aggregate performance of TAIEX traders is negative and does not consistently improve with experience. This finding illustrates that, generally speaking, trading by individuals in TAIEX futures is wealth-destructive behavior. Furthermore, like Ross (1973, 1975), we find that a large proportion of novice traders trade on a small scale and quickly stop trading

3 Glaser and Weber (2007) find that many investors think they make money though they often did not.

after realizing they are inept. This finding shows that people can learn about their ability, thus supporting the rational learning model (Mahani and Bernhardt, 2007; Nicolosi, Peng, and Zhu, 2009; Seru, Shumway, and Stoffman, 2009). However, those who remain in the market do not quickly learn from trading. The reasoning behind this result is that unprofitable traders trade over half of all TAIEX futures. Furthermore, losing traders continue to perform poorly, but profitable traders do not have persistent performance until they have accumulated a large number of trades - that is, traders have difficulty in improving their performance through learning (learning-by-doing).

A substantial part of learning overall involves learning about one’s abilities instead of learning to improve one’s performance. Although some traders can learn from trading, the speed of learning from trading is irritatingly slow. This finding indicates that traders have limited rationality. The possible reasons why a large population of TAIEX futures traders continue to lose money and still trade in the market are: (1) traders trade, because they are risk-loving or can obtain utility from gambling (Teweles and Jones, 1987; Hartzmark, 1991); (2) the self-attribution bias leads traders to become overconfident and overestimate their ability to forecast price trends (Strahilevitz, Odean, and Barber, 2011); and (3) because of the confirmation bias, people tend to remember their profit experiences and ignore their loss experiences (Teweles and Jones, 1987).

In the following subsection we review the literature and form testing hypotheses. Section 3 introduces the data. Section 4 presents the results of the tests relating to experience and performance, examines the performance persistence for each group, and explores whether unprofitable traders remain trading in the market or learn to leave the market. Section 5 is the conclusion.

2. Literature review and testable hypotheses

2.1 Literature review

Market participants can learn in two specific ways: “learning by doing” and “learning about their inherent ability.” In the spirit of the rational learning model (Arrow, 1962; Grossman, Kihlstrom, and Mirman, 1977; Seru, Shumway, and Stoffman, 2009), traders might improve their ability through trading. An alternative way is that traders learn about their inherent ability (Mahani and

Bernhardt, 2007; Linnainmaa, 2011). Traders are uncertain about their abilities and learn as they trade. If they infer from trading that they have skills, then they will subsequently trade more. In contrast, if they infer a low level of ability, then they stop trading.

In a seminal work on learning-by-doing, Arrow (1962) shows that “learning is the product of experience, and it can only take place through the attempt to solve a problem and therefore only takes place during activity.” Dhar and Zhu (2006), Nicolosi, Peng, and Zhu (2009), and Seru, Shumway, and Stoffman (2010) posit that traders learn how to trade through sharpening their trading skills or by learning to avoid trading errors. This way of learning leads traders to adjust their trading strategies in response to profits. Although their profits improve with experience, they potentially increase at a decreasing rate. Feng and Seasholes (2005) and Dhar and Zhu (2006) provide empirical evidence for the learning-by-doing effect. These studies find that traders can learn through experience and do not exhibit behavioral bias, such as the disposition effect. Kaustia, Alho, and Puttonen (2008) show that experienced traders are less likely to suffer from anchoring effects. Nicolosi, Peng, and Zhu (2009) show that traders’ performance improves considerately as their experiences increase. Similarly, Barrot, Kaniel, and Sraer (2014) note that experienced equity retail traders outperform less experienced traders. They argue that traders learn better trading skills through trading experience.

In the learning-about-ability models of Linnainmaa (2011) and Mahani and Bernhardt (2007), traders are heterogeneous with some being skilled and others unskilled. Traders initially do not know their own abilities and learn by observing their trading profits. Traders update their behaviors by following a Bayesian rule where they learn from their historical trading performance and change their strategies accordingly. Most traders recognize their lack of financial acumen and thus only trade small amounts when entering a market. Only a small fraction of traders is adept at identifying profitable trading opportunities. Once traders receive a set of negative signals to notify their lack of trading skills, they cease trading. An investor who receives positive signals continues to trade and trades more.

2.2 Testable hypotheses

A number of studies provide empirical evidence about learning from trading.

In the context of behavioral biases, Feng and Seasholes (2005) provide evidence that traders, in aggregate, display significantly less of a disposition effect over time. They estimate that for sophisticated traders, the disposition effect is essentially attenuated after about 16 trades. Similarly, List (2003) finds that experience can play a significant role in eliminating judgment errors, such as the endowment effect. Nicolosi, Peng, and Zhu (2009) posit that the trading performance of individuals improves with trading experience. Seru, Shumway, and Stoffman (2009) analyze the trades by individuals in Finland and also find that as traders become experienced, the disposition effect decreases and performance improves.

If traders are rational learners, then they should adjust their trades according to their inferred ability. Traders with more experience should have more past trading activities so as to help them infer their ability. Therefore, their inferences should be more accurate and lead to better trading decisions and hence better performance. In particular, Mahani and Bernhardt (2007) argue that experience should engender wisdom that improves performance over time. Linnainmaa (2011) also posits that a larger proportion of traders who remain trading in the market are skilled, because a skilled trader is more likely to survive. Therefore, more experienced traders perform better due to this learning-by-doing mechanism. We therefore form the first hypothesis as follows.

H1: More experienced traders outperform less experienced traders.

Another hypothesis with regards to learning-by-doing is performance persistence, with studies on futures markets finding that most traders lose money after taking into account commissions. Barber *et al*. (2004) find a similar result in stock markets. Some researchers have proposed several behavioral reasons to explain why traders take on such apparent wealth-destructive activities. Teweles and Jones (1987) and Hartzmark (1991) argue that traders prefer to take risk and obtain utility from gambling-type activities. Other researchers argue that because of the confirmation bias, traders tend to remember profits, but forget losses (Teweles and Jones 1987). The self-attribution bias also leads traders to become overconfident about their trading acumen (see Barber *et al*., 2004; Strahilevitz, Odean, and Barber, 2011). Thus, the behavioral learning model predicts that traders who make money become more confident and thus trade more actively, thereby causing worse subsequent performance. However, Mahani and Bernhardt

(2007) argue that behavioral reasons alone cannot completely explain traders' wealth-destructive behaviors. For instance, risk-loving alone cannot explain why poorly performing traders quickly exit the market. Selective recall does not reconcile the exit of poorly performing traders and the expansion of trading by better performing traders.

Coval *et al*. (2003) show that a portion of individual traders can achieve persistent excess returns. Nicolosi, Peng, and Zhu (2009) argue that individual traders become better traders over time if they trade more actively, and that their experience helps them improve performance. Studies like Coval et al. predict that rational Bayesian learning can forecast the persistence of traders' performance. In sum, learning-by-doing indicates that the persistence of performance improves over time for traders who remain active (Mahani and Bernhardt, 2007; Nicolosi, Peng, and Zhu, 2009; Seru, Shumway, and Stoffman, 2009). Thus, we form the second hypothesis as follows.

H2: Performance persistence improves with experience.

In addition to learning to improve their ability, traders can also learn about their ability. Specifically, as rational traders experience a series of losses, they might realize that their inherent level of ability is low and hence decide to stop trading. Learning-about-ability predicts that losing traders stop trading actively, while profitable ones remain in the market and increase their trading intensities over time (Linnainmaa, 2011; Mahani and Bernhardt, 2007; Seru, Shumway, and Stoffman, 2009). Seru, Shumway, and Stoffman (2009) provide compelling evidence that some traders improve their trading ability with experience, while others stop trading after realizing their poor ability at trading. Linnainmaa (2011) also posits that traders with less skill learn to exit the stock market, whereas Barber et al. (2011) find that unprofitable traders do not leave the market *quickly*. Therefore, we propose the third hypothesis as follows.

H3: Unprofitable traders stop trading quickly.

In addition to stop trading, if individual investors are able to infer their trading ability from their trading history and believe they are good (bad) at trading, then they are likely to trade more (less) actively. If investors learn from trading relatively quickly, then they may optimally choose to trade more actively, and thus the "excessive" trading documented by Odean (1999) and Barber and Odean (2001) is justified (Seru, Shumway, and Stoffman, 2009). In addition, traders can become overconfident after a good performance and consequently trade more actively. Due to self-attribution, good performance may lead to overconfidence and thus more trading, while poor performance does not necessarily lead to less trading. Thus, the rational learning hypothesis predicts that, in aggregate, individual speculators trade more (less) actively after good (bad) performance, while the behavioral learning hypothesis predicts that investors with previous net gains will increase their trade sizes, whereas losers will not decrease them. Therefore, the finding by Nicolosi, Peng, and Zhu (2009) and Linnainmaa (2011) - that good-performing investors increase subsequent trading intensity - can incur due to both rational and behavioral reasons. To know whether investors rationally learn their ability, we need to test the trading intensity following a bad performance. The fourth hypothesis thus follows.

H4: Traders with previous net losses decrease their trade intensity.

3. Data and method

3.1 Data

The data herein cover all futures contracts on TAIEX between January 2004 and December 2008 and come from the Taiwan Futures Exchange. The TAIEX is the first index to be traded in Taiwan and comprises all of the stocks traded on the Taiwan Stock Exchange (TWSE) and has the most active futures contracts. Each TX tick represents NT$200 (rough US$6.2) times the TAIEX index value. TAIFEX does not have designated market makers, and its transaction tax decreased from 0.025% to 0.01% after January 1, 2006.[4] The daily price limit during the sample period is +/-7% the previous day's settlement price. Before November 2008, the final settlement day is the third Thursday in each settlement month. The settlement price is the average price of the underlying index within the first 15 minutes after opening on the final settlement day. After November 2008, the final settlement day is the third Wednesday in each settlement month. The daily settlement price is the average price of the underlying index within the last 30 minutes before closing on the final settlement day.

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[4] Some individual investors might be hedgers. However, the TAIFEX codes every trader uniquely, and thus we cannot combine the futures data with the spot data. Due to data availability, we neglect the spot market and focus on the futures market.

Figure 1 illustrates the TAIEX index during the sample period. The figure shows that traders went through both bull and bear markets during the sample period. The index rose from about 6,000 index points at the beginning of the sample period to a high of 9,809.88 index points on October 29, 2007 and then sharply dropped to 4,089.93 index points by November 20, 2008.

The data comprise the trader's ID code, identifiers for the buying trader and the selling trader, the price, the volume, and the time of each transaction. Each record also has an account number that allows us to identify each trader's identity and also to correctly identify the trade type for each transaction, such as open buy, open sell, close buy, or close sell. We can construct a complete history of each investor's trading (position and prices) by linking orders with the trader's ID code. This history enables us to examine each investor's trading behavior and performance in TAIEX futures.

We only focus on trades that individual traders execute and exclude trades by institutional and proprietary traders.[5] The reason is that many institutions employ multiple traders who trade in rotating shifts. Thus, the trades by institutions reflect the behaviors of more than a single individual, therefore distorting the analyses of individual behavioral biases.[6] To clarify the effects of learning, we consider only individuals who begin trading after January 1, 2005 in the sample period as "new traders" or "new accounts." After filtering, the observations of round-trip transactions are 20,523,848, and the numbers of individual accounts are 104,357.

Figure 2 shows the number of accounts that place one or more trades in each year, additions of new accounts, and exiting accounts. There are considerable variations in the number of accounts placing trades over time, from 86,502 accounts in 2004 to as low as 53,106 in 2007 and as high as 67,219 in 2008. The

5 Some individual investors might be hedgers. However, the TAIFEX codes every trader uniquely, and thus we cannot combine the futures data with the spot data. Due to data availability, we neglect the spot market and focus on the futures market.

6 Individual investors and institutions can differ in their level of sophistication in response to information. The literature usually uses these two investor groups to identify the effects of traders' sophistication (e.g., Chakravarty, 2001; Collins, Gong, and Hribar, 2003; Elsharkawy and Garrod, 1996). Since we intend to understand whether individual traders learn from their trading experience, we restrict our sample to individuals who first enter the market and exclude institutions.

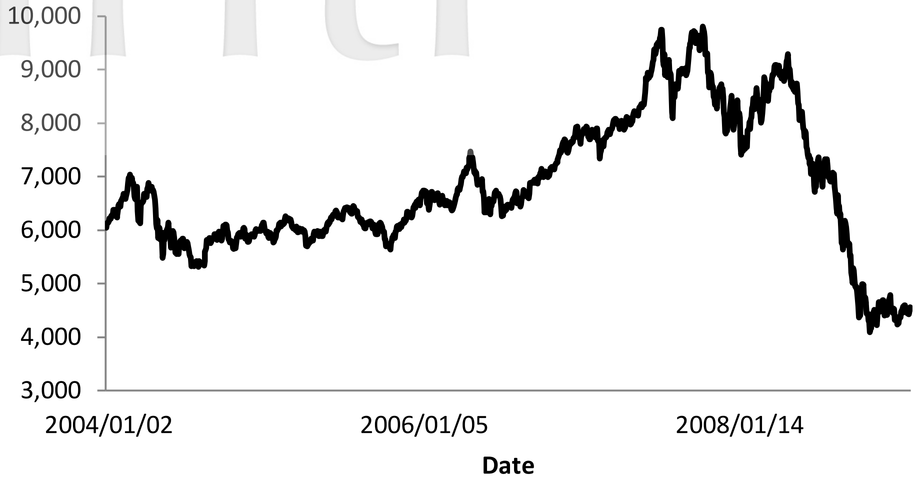

Figure 1
TAIEX index during the sample period

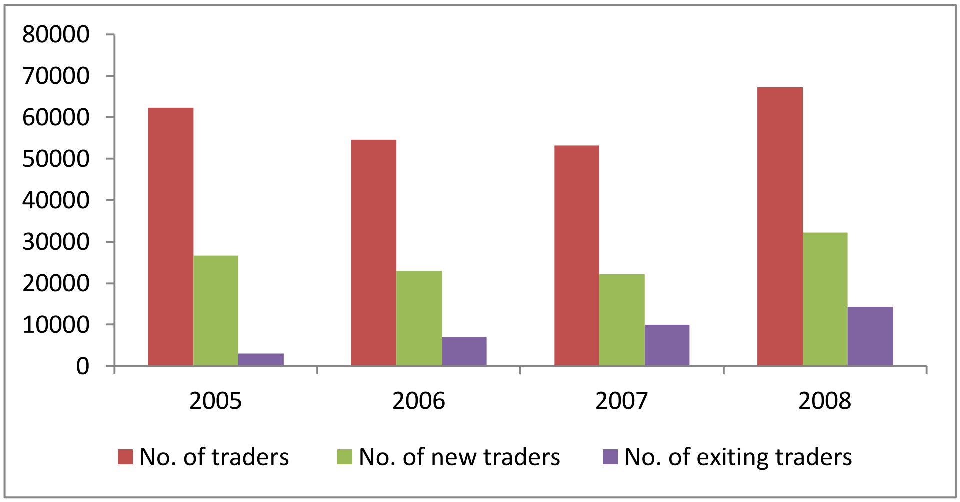

Figure 2
Numbers of participation by year

This graph shows the number of accounts (including both new and existing accounts), new accounts, and exiting accounts that place one or more trades in each year. There are considerable variations in the number of accounts placing trades over time, from 62,337 in 2005, down to a low of 53,127 in 2007, and up to a high of 67,277 in 2008. There is also a considerable variation in the number of new accounts over time, from 26,580 new accounts in 2005 down to a low of 23,011 in 2007, and up to a high of 32,220 in 2008. The leaving accounts increase from 3028 in 2005 to 14,333 in 2008.

addition of new accounts follows a similar pattern. The number of new traders also varies over time from 26,580 new accounts in 2005 to as low as 23,011 in 2007 and as high as 32,220 in 2008. The exiting accounts increase from 3,028 in 2005 to 14,333 in 2008. These numbers indicate that many traders enter and exit the market each year.

3.2 Summary statistics

Table 1 provides the summary statistics. Over the sample period, individuals lose money in the futures market with average losses of NT$385.1 per contract. The median value is also negative (NT$-8.6). The mean and median values of the total profits per trader are also negative. These statistics indicate that more than 50% of the trades by individuals are unprofitable. Specifically, 43,216 traders make money, and 97,141 traders lose money during the sample period. In addition, the average and median transaction volumes per trade are 1.7 and 1.0 contracts, respectively. The mean of the cumulative numbers of trades is 193.4, but their median value is 23. These numbers reflect that most individual traders

Table 1
Summary statistics

This table presents summary statistics of new individual traders for the dataset. Contracts per trade denoted as the numbers of contracts put on each trade. Total profits are accumulated total profits since an investor started trading. Experience is presented by either cumulative numbers of trades or days in the markets. Profits are denominated as NT$. There are 43,216 investors who make money, and 97,141 investors who lose money in the sample period. "Stdev" is standard deviation, and "OBs" is numbers of observations.

	Profits per contract	Contracts per trade	Total profits per contract	Cumulative numbers of trades	Days in the market
Mean	-385.1	1.7	-156,860.0	-4,985.3	193.4
25th	-61,459.8	1.0	-16,014.7	-5,818.0	5.0
Median	-8.6	1.0	-156,860.0	-1,472.2	23.0
75th	58,378.1	2.0	5,969.0	489.1	90.0
Stdev	294,522.0	2.0	3,199,321.5	18,132.1	2,450.9
OBs	20,523,848	20,523,848	140,357	140,357	140,357

trade one or two contracts, which means most of them are occasional traders.[7]

3.3 Method

We follow the approach of Lin and Chiang (2015) and construct a sequence of trades for each new account back to its first trade to calculate the net returns per contract. By tracing each account's trading history for each delivery month and marking each trader's positions to each trade, we can determine the gains and losses. We calculate the profits on round-trip trades and mark to market the other trades that remain open at the close of the trading day. We refer to these as gross profits. As a new long contract occurs, we first calculate the weighted average cost for each. When traders sell long contracts, the profit per contract is computed as the difference between selling prices and the weighted average cost per contract. The profits of short contracts are calculated similarly. We calculate paper gains and losses based on the settlement price and the weighted average cost per contract. For positions that are held until maturity and closed by the exchange, we calculate the realized gains or losses based on the final price of the contract.[8]

Following Seru, Shumway, and Stoffman (2009), we use two measures of trading experience. The first measure is the cumulative number of trades that a trader has placed in TAIEX futures. The reasoning is that traders might obtain investment experience by actively trading and observing the results of each trade. If traders mainly learn by this way, then cumulative trades can predict future performance.[9] The second measure is the months that an investor has been trading in the TAIEX market. Traders might also learn by observing market

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[7] Although the average of the individual traders is poor, this average is not necessarily inconsistent with the learning model of Mahani and Bernhardt (2007). The reasoning is that many novice investors enter and exit the market each year (Figure 2). In their model, inexperienced traders lose while those that are experienced profit; if the aggregate profits by experienced traders can cover the aggregate losses by inexperienced investors, then the aggregate performance is positive.

[8] To calculate net profits, we subtract the commission and transaction tax, which is 0.25% of the transaction value before January 1, 2006, 0.1% of the transaction value between January 1, 2006 and October 5, 2008, and 0.04% of the transaction value after October 6, 2008. The commission varies among the brokerage houses and the average is about NT$150 for each contract longed and each contract shorted.

[9] If investors mainly learn by actively trading and observing the results of each trade, then the cumulative trades can predict future performance even for noisy orders and arbitrage orders.

information like price and quantities, and by comparing which information source is more profitable. If this is the primary way in which traders learn, then months of trading experience is a better predictor of performance.

In order to estimate the shape of the performance-experience nexus in more details, we use a semi-parametric regression model. In this model we run the performance experience relation non-parametrically to avoid any functional form assumption on this relation, while the other variables enter parametrically. Specifically, we run the following semi-parametric model:

$$R_{i,t} = \beta_0 + \beta_1 f(Exp_{i,t}) + \delta_1 R_{i,t-1} + \delta_2 StdR_{i,t-1} + \delta_3 Vol_{i,t-1} + \varepsilon_{i,t}, \quad (1)$$

where $R_{i,t}$ is the dollar profits per contract for trader *i* in month *t*; $Exp_{i,t}$ is either the log cumulative numbers of trades or months in the market for trader *i* in month *t*; *f* denotes a generic smooth function that represents the performance experience relation after controlling for the parametric effects of the other variables. In the specification, we control for the average dollar profits per contract over the prior month ($R_{i,t-1}$), the standard deviation of dollar profits over the prior month ($StdR_{i,t-1}$), and the log trading volume over the prior month ($Vol_{i,t-1}$). The model is estimated using Yatchew's (1998) differencing method.

To examine whether performance is persistent, we follow Brown and Goetzmann (1995) and Brown, Goetzmann, and Ibbotson (1999) to compare the performance in the current period with that in the previous period. We construct a contingency table of profitable (P) and unprofitable (U) traders. We denote PP as profitable in both prior and current periods and UU as unprofitable in both periods. Here, PU (UP) is the number of profitable (unprofitable) traders in period t who were also unprofitable (profitable) in period t-1. We also denote a cross-product ratio (CPR) as (PP*UU)/(UP*PU), which captures the ratio of traders that show persistence in performance to the ones who do not show persistence. When there is no persistence, we can expect one of the four categories, PP, PU, UU, and UP, to take up 25% of the numbers of traders. Thus, the null hypothesis that performance in the first period is unrelated to that in the second period corresponds to an odd ratio of one. To ascertain whether profitable and unprofitable traders show different patterns of performance persistence, we further separate CPR into profitable (WCPR = PP/UP) and unprofitable traders

(LCPR = UU/PU).

To test whether past profitability affects the decision to quit TAIEX trading, we estimate the Cox proportional hazard rate model. The Cox proportional hazard model does not assume the probability of closing positions at time *t* after the open position and uses a non-parametric estimate of the baseline hazard. It is performed with time-varying covariates. Following Barber et al. (2011), we use the Sharpe ratio to assess the effect of past performance on exit decisions. The Sharpe ratio is defined as the dollar profits per contract divided by the standard deviation per contract. We construct a series of 21 dummy variables corresponding to the following ranges: (-∞, -0.50], (-0.50, -0.45], … , (0.45, 0.50], and (0.50, ∞). We set the range (0, 0.05] as the default category and add the remaining 20 dummy variables (*DSharpe*) as covariates when estimating the Cox proportional hazard rate model. The time-varying covariates include some variables associated with trading characteristics, such as trading frequency (*Frequency*), the ratio of long positions (*RLT*), and the cumulative numbers of trades (*Exp*). Frequency is defined as the numbers of contracts divided by the days in the market. Specifically, we estimate the following Cox proportional hazards model:

$$h_i(t) = h_{i0}(t)[\exp(\beta_0 + \beta_1 DSharpe_{i,t} + \beta_3 Frequency_{i,t} + \beta_4 RLT_{i,t} + \beta_5 EXP_{i,t}] \text{ , (2)}$$

where t is the time before they leave the market, and i is the i^{th} trader. The exponential term allows the hazard rate to vary across traders according to their performance and characteristics.

4. Empirical results

In this section we first examine the relation between experience and performance to test whether or not individual traders learn by trading. Second, we conduct a test of performance persistence. To test the existence of learning about their ability, we also explore the exit decisions and investigate whether the response to trading performance varies with experience.

4.1 Experience and performance

We start the analysis by separating the sample into six groups based on their experience. In each group we analyze their average dollar profits per contract across the different groups. If profits per trade are substantially higher in the more experienced groups than in the less experienced groups, then we can obtain a preliminary answer on whether traders rationally learn from trading. Table 2 shows the results. The empirical results present that the performance of TAIEX individual traders is unstable. For example, their performance improves at an initial stage of less than 5,000 contracts, but deteriorates afterwards. They do not make positive profits until they accumulate abundant trading experience at over

Table 2
Performance conditional on experience

This table reports the relationship between two proxies for experience (cumulative numbers of trades and months in the market) and their performance. The performance is measured in terms of average profits per contract. Traders are categorized into six groups based upon the cumulative number of trades or the number of months in which they trade. The performance is calculated by weighting the contracts they trade for each subgroup.

	Mean of profit	Median of profit	Numbers of observations	Numbers of traders
Panel A: Cumulative numbers of trades				
Contracts≦1,000	-570.6		8,981,851	140,357
1,000< Contracts ≦3,000	-231.1		3,130,031	5,836
3,000< Contracts ≦5,000	-95.4		1,288,904	1,705
5,000< Contracts ≦10,000	-447.3		1,535,000	952
10,000< Contracts ≦20,000	-1,079.6		1,319,957	391
Contracts >20,000	42.0		4,268,105	174
Panel B: Months in the market				
Months ≦3	115.6		4,580,783	140,357
3<Months≦6	-411.5		3,922,286	53,141
6<Months≦12	-766.5		4,545,192	37,767
12<Months≦24	-441.8		4,895,125	24,003
24<Months≦36	-297.4		1,985,876	10,833
Months>36	-978.8		594,586	4,244

20,000 contracts. This finding indicates that the speed of learning from trading is irritatingly slow.

Measuring experience by the months in the market provides a different pattern. In particular, traders on average make money in their first three months. As their trading continues, they lose money. This phenomenon holds even for traders who have more than three years of trading experience. In sum, traders in TAIEX futures fail to learn by observing market information, and the poor aggregate performance of individual traders is not consistent with the rational learning model of Mahani and Bernhardt (2007).

These results do not control for other trading characteristics that might affect traders' profits. Moreover, the profits per contract across various experience levels indicate that there is a non-linear relation between performance and experience. Therefore, Table 3 shows the estimation results for the parametric effects that control for other trading characteristics. As the table shows, traders'

Table 3
Semi-parametric analysis of experience and return

This table reports the parametric estimate for the following semi-parametric model:

$$R_{i,t} = \beta_0 + \beta_1 f(Exp_{i,t}) + \delta_1 R_{i,t-1} + \delta_2 StdR_{i,t-1} + \delta_3 Vol_{i,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is dollar profits per contract for investor *i* in month *t*; $Exp_{i,t}$ is either log cumulative numbers of trades or months in the markets for investor *i* in month *t*. In the specification, controlling variables include average dollar profits per contract over the prior month ($R_{i,t-1}$), standard deviation of dollar profits over the prior month ($StdR_{i,t-1}$), as well as log trading volume over the prior month ($Vol_{i,t-1}$). The values in parenthesis are t-values. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. The model is estimated using Yatchew's (1998) differencing method.

	Cumulated numbers of contracts	Months in the market
Intercept	-12.996	-6.143
	(-12.78***)	(-9.94)***
$R_{i,t-1}$	0.130	0.127
	(21.84***)	(21.44)***
$StdR_{i,t-1}$	-0.046	-0.044
	(-35.79)**	(-34.94)**
$Vol_{i,t-1}$	-1.462	-0.203
	(-5.77***)	(-1.03)

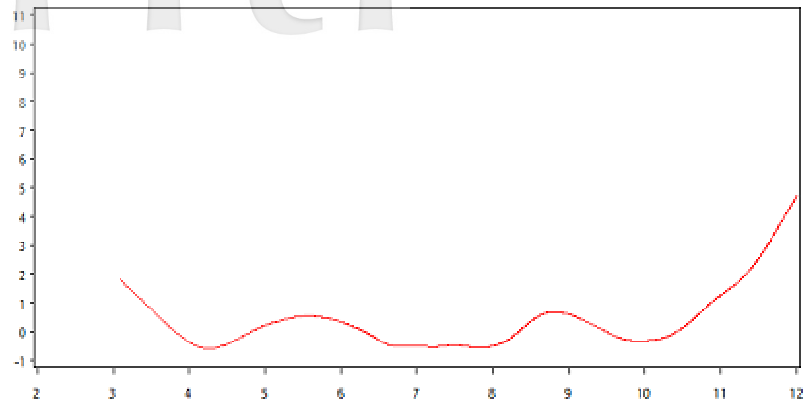
average profits per trade over the prior month have significant and positive effects on their subsequent profits. However, the standard deviation of their profits per contract and trading volume over the prior month are negatively correlated with profits per contract in the subsequent month. The significantly positive coefficients for traders' average profits per trade over the prior month disclose persistence in their performance. This result also confirms the view of Coval, Hirshleifer, and Shumway (2005) that while the average performance of individual traders is quite poor, good (bad) performers persistently outperform (underperform) others. The negative coefficient for the return volatility over the prior month indicates that traders with unstable trading performance are more likely to obtain worse returns in the future. Furthermore, a higher trading volume leads to worse returns, which is consistent with the prediction of overconfidence.[10]

Figure 3 presents the functional form of *f(Exp)*, which represents the relationship between experience and performance after removing the parametric effects of other variables. The results are similar to the analysis in Table 2. Specifically, when we measure experience in terms of the log cumulative numbers of contracts, TAIEX traders initially learn from trading at a decreasing rate, but the spine shape of the performance experience relation indicates that they do not consistently learn from trading. We find similar results when we measure experience in terms of months in the market. This result, to some degree, contradicts Nicolosi, Peng, and Zhu (2009). They estimate their regressions with data from a large discount U.S. brokerage firm and show that the trading performance of individuals improves with their trading experience.

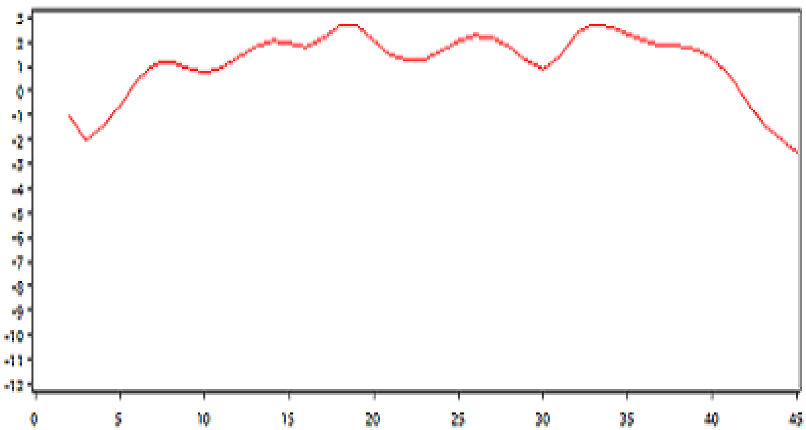
4.2 Experience and performance persistence

Another prediction of learning-by-doing is that traders' performance can persist. We follow Brown and Goetzmann (1995) and Brown, Goetzmann, and Ibbotson (1999) to examine the relation between experience and performance persistence. We measure experience with the quarterly cumulative numbers of contracts. We divide experience into six groups: (1) Contracts≦1,000, (2) 1,000<Contracts≦3,000, (3) 3,000<Contracts≦5,000, (4) 5,000<Contracts≦

[10] Chang *et al.* (2012) show that investors' sentiments influence their trading behavior, and both of them exhibit pronounced herding tendency.



Panel A: Log cumulated numbers of contracts and profits per contract



Panel B: Months in the market and profits per contract

Figure 3
Relationship between experience and profits per contract

This figure plots the estimated functional form of $f(Exp)$ in the model:

$$R_{i,t} = \beta_0 + \beta_1 f(Exp_{i,t}) + \delta_1 R_{i,t-1} + \delta_2 StdR_{i,t-1} + \delta_3 Vol_{i,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is dollar profits per contract for investor *i* in month *t*; $Exp_{i,t}$ is either log cumulative numbers of trades or months in the markets for investor *i* in month *t*. In the specification, controlling variables include average dollar profits per contract over the prior month ($R_{i,t-1}$), standard deviation of dollar profits over the prior month ($StdR_{i,t-1}$), as well as log trading volume over prior month ($Vol_{i,t-1}$). The model is estimated using Yatchew's (1998) differencing method.

10,000, (5) 10,000<Contracts≦20,000, and (6) more than 20,000. We also separate months in the market (months) into six groups: (1) Months≦3, (2) 3<Months≦6, (3) 6<Months≦12, (4) 12<Months≦24, (5) 24<Months≦36, and (6) more than 36 months.

Table 4 reports the test statistics for the odds ratio test. The results provide strong evidence of performance persistence. However, the persistence mainly comes from unprofitable traders, who continue to lose money. The less than one odds ratio for WCPR shows that the majority of prior profitable traders do not keep making money in the next period. The only exception is profitable traders with more than 20,000 cumulative trades, who show a tendency of positive performance persistence.[11] Overall, this result indicates that traders learn how to consistently make money relatively slowly, which to some degree contradicts Mahani and Bernhardt (2007) who argue that experience should engender wisdom that results in improved performance over time in which experienced traders display positive and persistent performance.

4.3 Exit decision

Traders can learn to realize that their inherent ability is inferior and hence decide to cease trading. This subsection examines whether traders who learn that their inherent ability is inferior decide to cease trading (learning about ability). If people can rationally learn about their ability, most losing traders will leave the market after they experience a short history of losses. However, a behavioral learner who loses might not learn quickly enough to exit the market. We estimate the survival rate of individual traders to understand whether losing traders quickly cease speculation after disappointing outcomes. We consider an individual trader as stopping trading if he or she has no trades for 12 consecutive months. Due to this requirement, we do not analyze individual traders who begin trading in 2008 since we cannot reliably determine whether or not they have stopped.

As argued by Mahani and Bernhardt (2007) and Seru, Shumway, and Stoffman (2009), low-ability traders realize that their inherent level of ability is low and decide to stop actively trading. Figure 4 shows the accumulated numbers of contracts placed before they leave the market. This graph shows that 13% of

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[11] We find similar results based on monthly frequency and different measuring intervals.

Table 4
Experience and performance persistence

This table identifies a trader as profitable (P) one if he (she) made positive profits in quarter *t-1*, and as unprofitable (U) one if he (she) made negative profits in quarter *t-1*. Thus, PP (UU) is the number of profitable (unprofitable) traders in quarter *t* who were also profitable (unprofitable) traders in quarter *t-1*. PU (UP) is the number of profitable (unprofitable) traders in quarter *t* who were also unprofitable (profitable) traders in quarter *t-1*. Cross-product ratio (CPR) reports the odds ratio of the number of repeat performers to the number of those who do not repeat; that is, (UU*PP)/(UP*PU). The t-statistics are calculated as the log odds ratio divided by its standard error, $\sqrt{\frac{1}{PP}+\frac{1}{PU}+\frac{1}{UP}+\frac{1}{UU}}$. CPR is further separated as WCPR = PP/UP profitable traders and LCPR = UU/PU for unprofitable traders. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	PP	PU	UP	UU	CPR	t-statistics	WCPR	t-statistics	LCPR	t-statistics
Panel A: Cumulative numbers of trades										
Contracts≦1,000	29,239	46,165	45,691	96,429	1.337	13.43***	0.640	-25.89***	2.089	56.52***
1,000< Contracts ≦3,000	2994	3967	4334	10378	1.807	8.51***	0.691	-6.76***	2.616	22.37***
3,000< Contracts ≦5,000	750	781	813	2012	2.377	5.71***	0.923	-0.69	2.576	9.75***
5,000< Contracts ≦10,000	627	596	659	1360	2.171	4.53***	0.951	-0.39	2.282	7.29***
10,000<Contracts≦20,000	358	270	278	479	2.285	3.25***	1.288	1.37	1.774	3.27***
Contracts >20,000	494	233	236	320	2.875	3.92***	2.093	4.05***	1.373	1.60
Panel B: Months in the market										
Months≦3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
3<months≦6	3486	8584	6727	17517	1.057	0.98	0.518	-13.68***	2.041	23.51***
6<months≦12	5743	8934	8688	18771	1.389	6.69***	0.661	-10.57***	2.101	25.09***
12<months≦24	9837	13508	12320	23593	1.395	8.35***	0.798	-7.23***	1.747	22.45***
24<months≦36	4572	5148	5649	9873	1.552	7.26***	0.809	-4.62***	1.918	16.45***
months>36	3032	3123	3597	7592	2.049	9.57***	0.843	-3.01***	2.431	18.15***

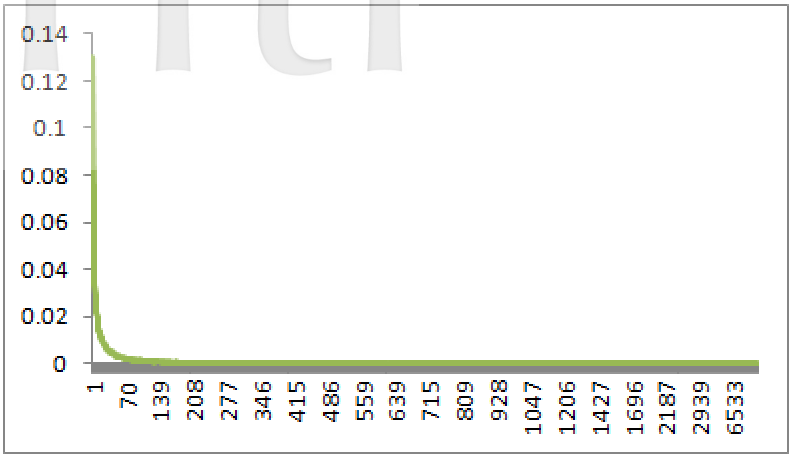


Figure 4
Accumulated numbers of orders placed before leaving the market

This graph shows accumulated numbers of contracts placed before they leave the market. Here, 13.00% of traders leave the market only after one transaction; 44.35% of traders leave the market before placing the 10^{th} contract; 74.92% of traders make the same exit decision before placing the 50^{th} contract; 85.35% leave before trading their 100^{th} contract.

traders leave the market after only one transaction; 44.35% of traders leave the market before placing 11 contracts; 74.92% of traders exit before placing 50 contracts; and 85.35% leave before placing 100 contracts. Figure 5 also provides evidence on the survival days before they leave the market: 14.29% of traders leave the market after the first day of trading; 18.29% of traders leave the market within one week; 30.92% of traders leave the market within one month; and 47.92% of traders make the exit within one quarter. Our results are consistent with Mahani and Bernhardt (2007) and Seru, Shumway, and Stoffman (2009) who state that some traders stop trading actively after realizing their poor trading ability.[12]

[12] The finding that average profits are positive within the first three months indicates that some new traders make money and others lose money; the aggregate positive returns dominate the aggregate negative returns. This domination does not violate the prediction of learning-about-ability that is related to the high proportion of losers who leave the market after a short history of losses.

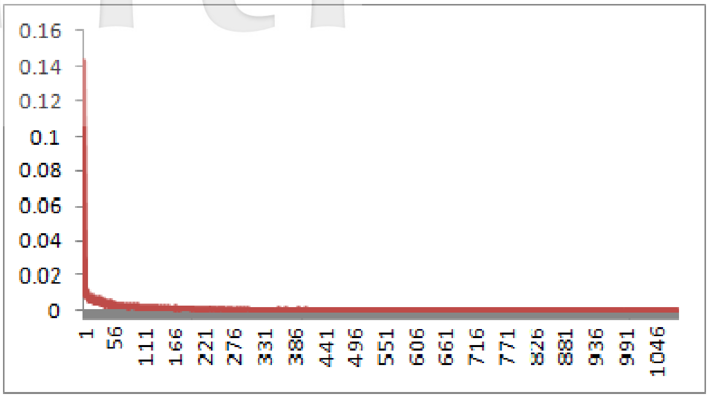


Figure 5
Days in the market before leaving the market

This graph shows survival days before traders leave the market. Here, 14.29% of traders leave the market after the first day of trading; 18.29% of traders leave the market within one week; 30.92% of traders leave the market within one month, and 47.92% of traders make the same exit decision within one quarter.

To test whether past profitability affects the decision to quit TAIEX trading, we estimate the Cox proportional hazard rate model. Figure 6 illustrates the results. The horizontal axis represents profit categories, while the vertical axis represents the hazard rate relative to the omitted Sharpe ratio category of (0,0.05]. The declining shape indicates that the Sharpe ratio of profitability is negatively related to the hazard rate. The figure shows that all hazard ratios of positive Sharpe categories are larger than one, but all are smaller than one for negative Sharpe ratios. Furthermore, the slope over the loss domain is steeper than that in the gain domain. This slope indicates that traders of TAIEX futures are more (less) likely to quit when faced with negative (positive) returns versus those with a minor positive performance like a Sharpe ratio between 0 and 0.05. This is in line with the prediction of the rational learning model that traders exit the market after realizing their poor trading ability (Linnainmaa, 2011; Seru, Shumway, and Stoffman, 2009).

4.4 Experience and response of trading to performance

Another important implication of the learning-about-ability model is that traders increase their trading intensities as they become more experienced, as in

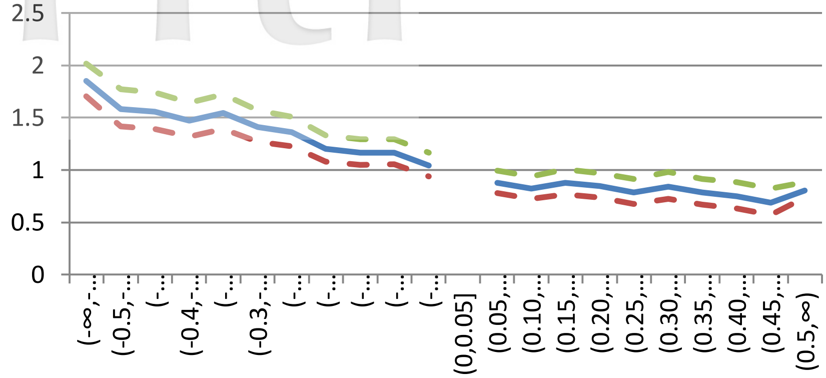


Figure 6
Hazard ratio for survival time of TAIFEX traders conditional on past profitability

The figure reports the hazard ratio for survival time and the 95% confidence interval (dashed lines) for different profit categories relative to the default category of (0.00, 0.05], where the hazard ratio is equal to one by construction. Profits are measured using the Sharpe ratio of returns - dollar profits per contract divided by the standard deviation of dollar profits per contract. The Cox proportional hazard rate model also includes controlling variables associated with trading characteristics, which include average dollar profits per contract over the prior month, standard deviation of dollar profits over the prior month, as well as log trading volume over the prior month.

Mahani and Bernhardt (2007). In other words, profitable traders will increase their trading volume in response to good signals about their ability. To test this prediction, we first calculate the changes in trading volume between the last quarter and the current quarter for each trader in each quarter.[13] Second, we split traders into two groups: profitable and unprofitable traders who earn positive and negative profits in the last quarter, respectively. Third, we split traders based on their prior experience into five broad categories. In addition to changes in trading volume, we also analyze the percentage changes in trading volume.

The results are reported in Table 5. Panels A and B respectively list the difference in the increase in trading volume (ratio of traders increasing in trading volume) between profitable and unprofitable traders when experience is measured in terms of the cumulative numbers of contracts and months in the

[13] We also calculate monthly changes in trading volume based on different measuring intervals for a robust check and find a similar result.

Table 5
Changes in trading volume conditional on experience and past profitability

The left (right) part of Panel A presents the difference of increase in trading volume (of the proportion of traders who increase their trading) from quarter *t-1* to *t* between profitable and unprofitable trader groups when experience is measured in terms of cumulative numbers of contracts. The left (right) part of Panel B presents the difference of increase in trading volume (of the proportion of traders who increase their trading) from month *t-1* to *t* between profitable and unprofitable trader groups when experience is measured in terms of months in the market. Profitable (unprofitable) traders are denoted as those who make positive (negative) money over the prior month. All values are presented in percentage terms. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	Increase trading volume						Ratio of traders increasing trading volume			
	Profitable traders		Unprofitable traders		Difference	t-values	Profitable traders	Unprofitable traders	Difference	t-values
	Mean	N	Mean	N						
All contracts	4.536	228,190	-1.262	288,158	5.797	4.18***	0.514	0.400	0.114	45.28***
Panel A: Cumulative numbers of contracts										
Contracts≦1,000	2.168	207,835	-0.156	258,712	2.324	31.71***	0.506	0.405	0.101	42.06***
1000< Contracts ≦3,000	13.490	13,340	-3.751	20,863	17.241	7.94***	0.509	0.340	0.169	15.23***
3000< Contracts ≦5,000	13.324	2,742	-11.750	4,015	25.074	2.57**	0.513	0.353	0.160	6.93***
5,000< Contracts ≦10,000	150.300	2,032	-91.550	2,758	241.900	1.76*	0.519	0.377	0.142	5.12***
10,000<Contracts≦20,000	32.217	1,061	-3.371	1,005	35.588	0.30	0.494	0.455	0.039	1.05
Contracts >20,000	23.022	1,180	-23.382	697	40.404	0.53	0.522	0.426	0.096	1.12
Panel B: Months in the market										
Months≦3	10.626	67994	2.417	83,002	8.208	2.67***	0.437	0.462	-0.025	-6.53***
3<Months≦6	1.816	48,404	-5.321	63,933	7.136	1.67	0.534	0.353	0.181	40.70***
6<Months≦12	2.378	52,591	-3.363	66,714	5.741	3.40***	0.515	0.382	0.132	30.78***
12<Months≦24	1.220	43,106	-0.032	52,677	1.252	0.89	0.513	0.399	0.113	23.81***
24<Months≦36	2.961	13,363	-0.776	17,605	3.737	2.08**	0.519	0.379	0.121	14.23***
Months>36	2.732	2,732	-0.702	4,227	3.405	2.09**	0.519	0.311	0.208	11.27***

performance than bad performance, TAIFEX traders seem to display a tendency towards overconfidence.

In addition to changes in trading volume, we also analyze the proportion of traders who increase their trading from quarter *t-1* to *t*. In the right part of Table 5, we find a similar and definite pattern: the ratio of profitable traders who increase their subsequent trading volume (0.514) is larger than that of unprofitable traders (0.400). We find similar results when we use different experience intervals. Overall, more than 50% of profitable traders choose to place more orders, and more than 50% of unprofitable traders choose to trade less actively. This finding shows that learning is an important feature of financial markets; traders who suffer from initial losses and learn that they have no informational advantage or skill trade less actively.

For a robust check, we estimate the proportion of trading that can be attributed to traders with a history of losses. First, we categorize traders at the beginning of each quarter based on their previous quarter's trading activity and profits. Second, similar to the procedure in Barber et al. (2011), we identify three groups of traders: (1) no prior trades, (2) unprofitable traders, and (3) profitable traders. No prior trades are those with no trading throughout the previous quarter. Unprofitable (profitable) traders are those who have negative (positive) profits per trade throughout the previous quarter.

Table 6 presents the proportions in each category. Panel A is the trading volume attributed to traders of each group, and Panel B is the number of traders in each group. An inspection of this table shows that the traders who temporarily leave the market after at least a quarter make up the smallest proportion of all trades (11.234%). Those ranked second are the profitable traders. However, although only 17.631% of the traders make money each quarter in the TAIEX futures market, they contribute 30.461% of the trading volume. The vast majority of trading comes from unprofitable traders, who represent 58.305% of all trades and 61.365% of the trading population in the sample period. However, the trade to population ratio for profitable traders (1.73=30.461/17.631) is higher than that of unprofitable traders (0.95=58.305/61.365). In this sense, unprofitable traders appear to rationally learn about their ability and trade less actively after a history of losses. This finding is similar to the results on stock trades in Linnainmaa (2011).

Table 6
Trading volume by traders with no prior trading, unprofitable traders, and profitable traders

This table reports trading volume made by traders with no prior trading, unprofitable traders, and by profitable traders. No prior traders are traders who do not trade in quarter *t-1*. Unprofitable (profitable) traders have negative (positive) profits per contracts net of costs in quarter *t-1*.

	No prior trades	Profitable traders	Unprofitable traders
Panel A: Percentage of trading volume			
Full sample	11.234	30.461	58.305
2005	10.643	28.700	60.657
2006	11.094	32.786	56.121
2007	9.202	34.066	56.732
2008	12.612	27.958	59.430
Panel B: Percentage of Traders			
Full sample	21.004	17.631	61.365
2005	20.058	19.013	60.930
2006	19.841	18.847	61.311
2007	20.170	19.454	60.377
2008	23.551	13.846	62.603

4.5 Traders' sophistication and learning from experience

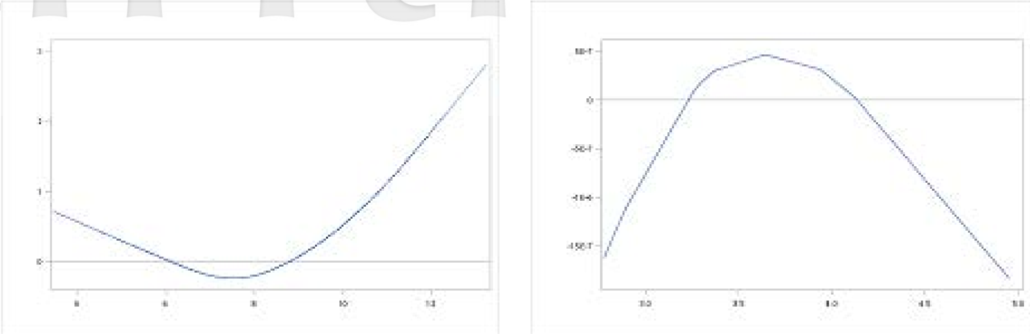
The final concern is which traders can better learn from experience. We test this by dividing traders into subsamples based on various characteristics that show their financial sophistication. In particular, we sort traders into quartiles by their wealth and the ratio of long positions. We use the subsamples to run the semiparametric regression model (1). We observe the difference in shapes across the figures to test whether learning across groups takes place at different rates. Similar to Feng and Seasholes (2005), we measure wealth by calculating the average number of new contracts per month. We classify traders as wealthy if they are in the top quartile and poor if they are in the bottom quartile. Choe and Eom (2009) show that less sophisticated traders are more likely to suffer from the disposition effect, and this effect is significantly stronger in long positions than in short positions. Therefore, we also use the ratio of long positions taken by the traders as a measure of sophistication.

Figure 7 reports the relation between the cumulative number of trades and profits per contract for various levels of trader sophistication. Panel A shows that wealthy traders display a U-shape pattern for the performance-experience nexus, but poor traders display an inverse U-shape. These shapes indicate that wealthy traders are more likely to learn from trading in the long run than poor traders. Panel B illustrates that traders with higher proportions of long contracts do not learn from trading in the long run. However, traders with lower long contract ratios have positive profits if their number of trades is large enough, although their initial performance is unstable.

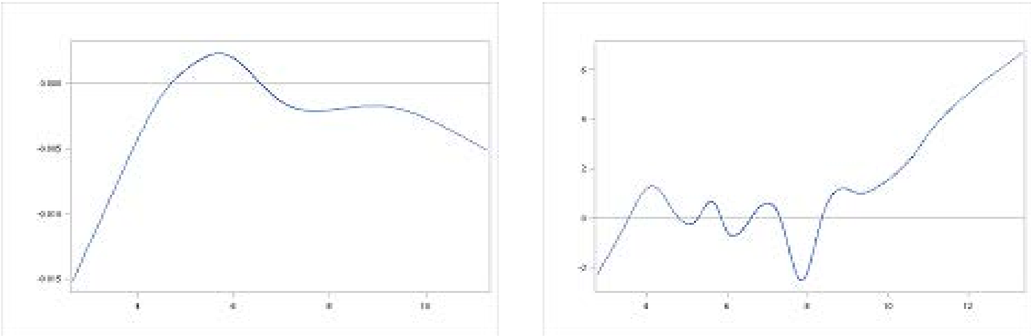
Figure 8 reports the relation between months in the market and profits per wealthy and poor traders have negative returns in the first year they are in the futures market. Subsequently, they earn positive returns, but the positive returns do not persist forever. Wealthy traders have a longer run (until 40 months) and poor traders have a shorter run (until 22 months) of positive returns. This difference reflects that the number of months in the market might not be a good way to learn. In comparison, wealthy traders can learn more by observing prices and quantities. Panel B illustrates that traders with higher proportions of long contracts do not learn from observing prices and quantities in the long run. Traders with a lower ratio of long contracts also show unstable performance when experience is measured by the number of months. Their performance initially improves, but deteriorates afterwards. However, they earn positive profits if they are in the market for as long as four years. This finding indicates that learning from trading is irritatingly slow. In sum, our results provide evidence that learning-from-doing mainly takes place among sophisticated traders like wealthy people and those who do not frequently put on long orders.

5. Conclusion

There are two specific ways in which traders can rationally learn. First, traders can improve their ability through trading (learning-by-doing); second, traders can realize that their inherent ability is inferior and decide to cease trading (learning-about-ability). This paper empirically investigates these two types of learning using individual traders' complete records of TAIEX futures contracts.



Panel A: Wealth (wealthy for the left figure, and not wealthy for the right figure)



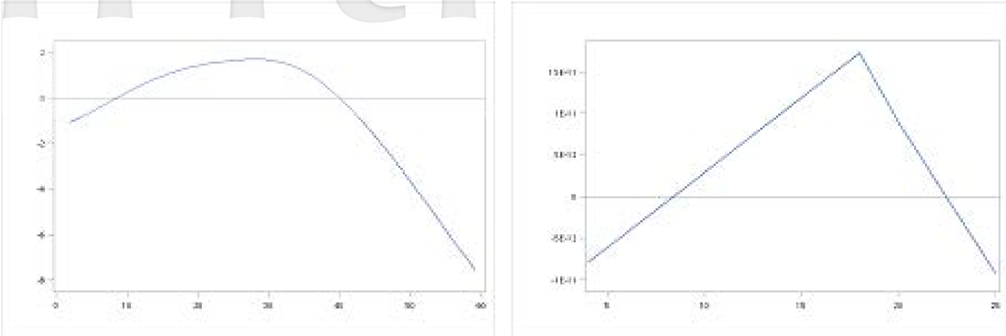
Panel B: Long contract ratios (high for the left figure, and low for the right figure)

Figure 7
Cumulative numbers of trades and profits per contract: By investor sophistication

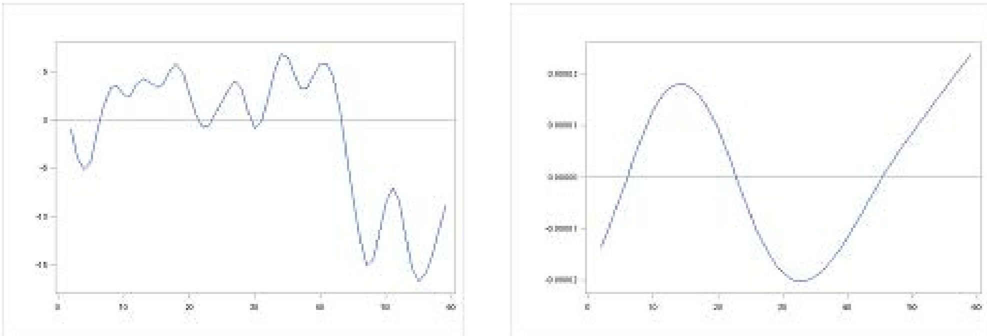
This figure plots the estimated functional form of $f\,(Exp)$ in the model:

$$R_{i,t} = \beta_0 + \beta_1 f\,(Exp_{i,t}) + \delta_1 R_{i,t-1} + \delta_2 StdR_{i,t-1} + \delta_3 Vol_{i,t-1} + \varepsilon_{i,t}\,,$$

where $R_{i,t}$ is dollar profits per contract for investor *i* in month *t*; $Exp_{i,t}$ is the log cumulative numbers of trades for investor *i* in month *t*. In the specification, controlling variables include average dollar profits per contract over the prior month ($R_{i,t-1}$), standard deviation of dollar profits over the prior month ($StdR_{i,t-1}$), as well as log trading volume over the prior month ($Vol_{i,t-1}$). The model is estimated using Yatchew's (1998) differencing method.



Panel A: Wealth (wealthy for the left figure, and not wealthy for the right figure)



Panel B: Long contract ratios (high for the left figure, and low for the right figure)

Figure 8

Months in the market and profits per contract: By investor sophistication

This figure plots the estimated functional form of $f(Exp)$ in the model:

$$R_{i,t} = \beta_0 + \beta_1 f(Exp_{i,t}) + \delta_1 R_{i,t-1} + \delta_2 StdR_{i,t-1} + \delta_3 Vol_{i,t-1} + \varepsilon_{i,t},$$

where $R_{i,t}$ is dollar profits per contract for investor *i* in month *t*; $Exp_{i,t}$ is the number of months in the market for investor *i* in month *t*. In the specification, controlling variables include average dollar profits per contract over the prior month ($R_{i,t-1}$), standard deviation of dollar profits over the prior month ($StdR_{i,t-1}$), as well as log trading volume over the prior month ($Vol_{i,t-1}$). The model is estimated using Yatchew's (1998) differencing method.

We find that the aggregate performance of individual traders is negative - that is, the majority of traders lose money; profitable traders do not exhibit persistence in performance; and traders' performance does not consistently improve with experience. The above evidence provides strong evidence that, on average, TAIEX futures traders cannot learn by doing. On the other hand, although unprofitable traders represent the major proportion of the trading and the population, a large proportion of losing traders quickly learn about their inability and cease trading. This learning explains the high turnover in the trading population of the TAIEX futures market.

These results indicate that people have limited rationality, and a substantial part of learning occurs when traders stop trading after learning about their poor inherent ability. Our results only partially support the learning model of Mahani and Bernhardt (2007). Their model contends that losing traders learn quickly and leave the market, and good performers expand their trading and have persistent performance. Nevertheless, our results are consistent with Seru, Shumway, and Stoffman (2009) – namely, that a substantial part of learning by trading is explained by learning-about-ability.

Learning is a dynamic non-linear process. At the initial stage, those who earn profits regard themselves as skilled and expand their trading activities, which in turn reduces their profits. We show that their positive profits are not persistent until they accumulate abundant trading experience, such as more than 20,000 round-trip transactions. This evidence indicates that experience is a double-edged sword. While traders learn their ability from experience, those who survive in the TAIFEX market reinforce their overconfidence through self-attribution. However, as unprofitable traders accumulate plentiful trading experience, they discount their trading ability and reduce their trading intensities.

Finally, one question is why some losing traders remain in the market. The persistent and poor performance for those who continue to trade indicates that behavioral biases play an important role in trading. For example, they might trade, partly because they are overoptimistic about the prospect of their success, or obtain non-financial utility from gambling. In addition, due to the self-attribution bias, they attribute successes to their abilities and failures to bad luck. Hindsight bias also induces them to idealize their memory of what they believed or forecasted in the past. Confirmation bias, the tendency to search out evidence consistent with one's prior beliefs and ignore conflicting data, also contributes to limited rationality. These behavioral biases provide explanations as to why some losing traders cannot learn quickly about their abilities and leave the market.

The implication for a policy maker is that allowing unskilled traders to learn their inferior abilities without incurring considerable costs is more valuable than encouraging new entrants to become active traders. In such cases, the policy maker could devise a screening mechanism or test to reveal a person's inherent trading ability.

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