Learning through trading:  
A risk perspective

Ming-Wei Hsu, Ming-Chien Sung, Tiejun Ma, Johnnie E.V. Johnson  
Centre for Risk Research, School of Management, University of Southampton,  
Highfield, Southampton, SO17 1BJ, UK

Abstract

We examine the degree to which individuals learn to improve their trading performance by analyzing 8,441,805 trades of 28,061 spread-traders over a 10 year period. With more experience, traders make higher returns but take greater risk, resulting in a lower risk-adjusted (Sharpe ratio) performance. The conclusion holds after accounting for selection bias and survivorship bias. To our best knowledge, this is the first study to examine learning effects using individual level empirical trading data from a risk perspective.

Keywords: Learning; Behavioral finance; Risk-adjusted performance.
1 INTRODUCTION

One of the fundamental assumptions of neoclassical economic theories is that individuals are rational and attempt to maximize expected utility (Ackert and Deaves, 2009). This assumption has been challenged by the widespread observation of a number of behavioral biases (Barber and Odean, 2001; Kahneman and Tversky, 1979; Montier, 2002; Shefrin and Statman, 1985). However, despite these behavioral biases, it is possible that individuals can learn from experience to improve financial decision making to the point where the assumptions of neoclassical theories hold. In fact, there is strong evidence indicating that individuals are likely to change their behavior with experience (Camerer and Hua Ho, 1999; Charness and Levin, 2003; Roth and Erev, 1995). The manner and degree to which they change their behavior remains a matter of debate. In particular, the rationality assumption would be justified if individuals can learn from experience to appropriately adjust their probability estimates and finally make rational, correct decisions; a process referred to as Bayesian learning (Charness and Levin, 2003; Chiang et al., 2011). On the other hand, if individuals engage in reinforcement learning, wherein they repeat behavior which was rewarding in the past, this would not justify the rationality assumption. Evidence from laboratory studies suggest that individuals engage in reinforcement learning (Charness and Levin, 2003; Roth and Erev, 1995), but little evidence is available from real world financial markets. This study attempts to redress this balance by exploring the manner and degree to which real-world traders adjust their behavior in the light of their previous experience.

The major contribution of this study is that we examine the degree to which traders learn to improve their trading behavior, taking account of the volatility of returns and their risk-adjusted performance. This, to the best of our knowledge, has not to date been examined with individual level empirical trading data.

The risk return trade-off in stock markets has been discussed extensively, and it is commonly agreed that high returns are accompanied by high risk (Fama and MacBeth, 1973; Glosten et al., 1993). Clearly, traders may increase returns by taking higher risk. It is our contention that assessing the performance of traders simply by
their returns may produce misleading conclusions concerning the degree to which traders learn from experience. Hence, we assess the degree to which traders improve their risk adjusted returns through time by measuring the changes in their Sharpe ratio, a widely used measure in the economic and finance literature, to adjust for risk (Sharpe, 1998). In addition, examining changes in the volatility of their returns and their risk-adjusted performance allows us to observe the effect of experience on the risk preferences of traders. As a result, we hope to shed light on the debate between neoclassical economic theories and behavioral theories.

The evidence we present suggests that traders do not learn to improve risk-adjusted performance. Rather, whilst experienced traders make higher profits, they suffer higher volatility of returns and decreases in risk-adjusted performance. Consequently, our results suggest that traders may not estimate the underlying risk correctly, and the ‘learning’ which takes place may involve altering behavior in a manner reinforced by the higher profits accompanying this riskier behavior.

This article is structured as follows. In the second section we discuss the extant learning literature. We describe the data and the methodology in the third section. In the fourth section we present our results. We discuss the results in the fifth section and this is followed by the conclusion.

2 LITERATURE

There has been much debate regarding the manner in which humans make decisions. Neoclassical economists assume that individuals are rational in making decisions. This approach led to the development of expected utility theory and the efficient market hypothesis. However, the rational assumption has been strongly challenged as several behavioral biases have been documented by psychologists and experimental economists (Barber and Odean, 2001; Bondt and Thaler, 1985; Gervais and Odean, 2001; Huberman and Regev, 2001; Kahneman and Tversky, 1979; Shefrin and Statman, 1985).

The rational assumption underlying the neoclassical approach suggests that individuals learn, i.e. update their beliefs concerning the probability of events, by following the Bayesian rule (Charness and Levin, 2003; Roth and Erev, 1995). That is, individuals update prior probability estimations conditional on new information or
events. On the other hand, psychologists find that ‘reinforcement’ can explain most of the dynamics of human behavior observed in the laboratory experiments (Roth and Erev, 1995). Individuals who learn by reinforcement make decisions based on previous outcomes: strategies which led to better outcomes in the past are more likely to be chosen. Most laboratory experiments suggest that reinforcement explains learning behavior better than Bayesian learning (Charness and Levin, 2003; Roth and Erev, 1995). However, there is still evidence showing that a certain percentage of individuals are consistent with the neoclassical view (Bruhin et al., 2010; List, 2004). Hence, there has been considerable effort in reconciling the two perspectives (Camerer and Huo Ho, 1999; Lo, 2004), and some empirical studies have been conducted to examine the effect of experience on individual financial behavior: Kaustia and Knüpfer (2008) find that Finnish IPO investors with higher past returns are more likely to subscribe to the next IPO than those with lower past returns. Similarly, Choi et al. (2009) show that individuals who have obtained higher returns or lower return variance from their 401(k) retirement fund in the past, tend to increase their 401(k) saving rate, and Glaser and Weber (2009) document that higher past returns lead to an increase of trading activities.

Most studies examining human decision making and learning in particular, have been conducted in the laboratory. The literature examining learning using empirical trading data is slowly expanding but the results of these studies are mixed. Nicolosi et al. (2009) and Linnainmaa (2011) find that traders make higher returns as they gain more experience. Similarly, Feng and Seasholes (2005) and Seru et al. (2010) find that traders make higher returns and display lower disposition effect as their experience increases. By contrast, Chiang et al. (2011) find that the returns of IPO investors decrease the more auctions in which they participate.

An important feature of this existing literature is that learning is measured by improvements in returns. By contrast, our study aims to develop our understanding of the manner and degree to which traders learn through experience by accounting for the risk inherent in their trading performance. This, to our best knowledge, has not been examined at the individual level using empirical trading data.

Hypothesis
Whilst there are some exceptions, previous research has generally found that experience and profitability are positively related (e.g., Seru et al., 2010; and Nicolosi et al., 2009). Consequently, we first test the following hypothesis:

Hypothesis 1: Traders with more experience have better returns.

Chiang et al. (2011) found that IPO traders become more aggressive, in terms of being more likely to bid a higher price, with more experience. In addition, Glaser and Weber (2009) show that traders with higher past returns take higher risk, in that they buy high risk stocks and reduce portfolio diversity. Based on the above findings, we test the following hypothesis:

Hypothesis 2: Traders take higher risk as they increase in experience.

If traders can estimate the risk and uncertainty rationally, they may, through learning, achieve higher returns without increasing risk or may maintain returns on the same level with lower risk. In either case their investment performance measured by Sharp ratio should be improved. We explore this conjecture by testing the following hypothesis:

Hypothesis 3: Traders achieve higher risk-adjusted investment performance as they gain in experience.

3 Methodology

3.1 Data

The data used in this study was collected from a large spread-trading broker based in the U.K. The data relates to 8,441,805 closed trades of 28,061 clients of the spread-trading broker, for the period October 2003 to March 2013. Spread trading is an important derivative market which has developed rapidly in the U.K. since the 1990s. This has arisen largely due to the relatively low transaction costs, the ease of access it provides to retail investors to international markets and risk management consideration (Brady and Ramyar, 2006; Paton and Williams, 2005).

Spread traders can either buy or sell the market (e.g. index) based on their individual prediction of the market movement. The profit and loss of each trade depends on the
investment amount and how many points the index rises or falls in the direction that the trader predicted. For example, if a trader believes that the FTSE 100 will rise, he might then ‘buy the index’ at, say, £50 per point. If the FTSE 100 rises 20 points and the trade closes his trade, he makes £1000 profit. If the FTSE 100 falls 10 points and the trade is closed, the trader’s loss is £500. Alternatively, traders can ‘sell’ the market, in which case profits are made if the market falls.

Spread trading data offers a number of advantages for the purpose of determining the degree and manner in which spread traders alter their behavior with experience. In particular, spread trading is short-term trading (Gultstawitchai et al., 2013), and on average in our data 3 or 4 the trades are closed within one hour. Consequently, all returns are realized and no estimation of gains is necessary. By contrast, individuals buying shares may have dividends in the future and often shares are held for the long term. Clearly, returns of stock purchases are not definite until sold, and, therefore, researchers often need to estimate the return of a stock purchase, and this process may lead to bias. For example, Seru et al. (2010) and Nicolosi et al. (2009) measure stock returns over a 20- and 30-day period respectively after each purchase, and Barber and Odean (2002) assume that all trades occur on the last day of the month in estimating monthly returns. On the contrary, all the spread trades are closed in our dataset, so the returns are realized and definite. Since less estimation is involved, spread trading data allows us to produce more definitive results.

Within the spread-trading database, each record contains the following information concerning a closed trade: an identification number related to an individual client, the trade opening time, closing time, opening price, closing price and investment amount. Variables, such as the measures of experience, risk and Sharpe ratios are calculated on a trade by trade basis.

Descriptive statistics related to the spread trading data are shown in Table 1. These statistics show that the mean number of trades placed by a trader (300.4) is significantly higher than the third quartile (190), which suggests that the total number of trades per individual right-screwed. This suggests that a small number of traders place far more trades than others. The distribution of the time duration between a trader’s first and last trade is also right-skewed (mean: 454.7, third quartile: 658). This suggests that we need to consider survivorship bias. The descriptive statistics shown in Table 1 also shows the generally short-term nature of spread-trading with
half of the trades being closed within 699 seconds (11.7 minutes) of their opening, and over 75% of the trades being closed within 1 hour.

Table 1 Spread Trading Data Summary
This table presents summary statistics of spread trade data used in this study.

<table>
<thead>
<tr>
<th></th>
<th>1st Qu</th>
<th>Median</th>
<th>Mean</th>
<th>3rd Qu</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traders’ Total Trade Number</td>
<td>10</td>
<td>46</td>
<td>300.4</td>
<td>190</td>
</tr>
<tr>
<td>Traders’ Active Period (in days)</td>
<td>24</td>
<td>185</td>
<td>454.7</td>
<td>658</td>
</tr>
<tr>
<td>Holding Time (in seconds)</td>
<td>180</td>
<td>699</td>
<td>19720</td>
<td>3113</td>
</tr>
</tbody>
</table>

3.2 VARIABLES

Experience

We follow Seru et al. (2010) and use trading time to measure the experience of traders. Let $k \in N^+$ represents a trader and $i \in N^+$ represents a trade, where $N^+$ is the set of non-negative integers. Let $t_{ik}$ represent the time when trader $k$ opens their $i^{th}$ trade. In our study, the experience associated with the $i^{th}$ trade of trader $k$, $E_{ik}$, is defined as the number of seconds between $t_{1k}$ and $t_{ik}$:

$$E_{ik} = t_{ik} - t_{1k}.$$  

Return

Return of the $i^{th}$ trade of trader $k$, $R_{ik}$, is defined as the number of points won or lost on that trade.

Risk

We measure risk by the variance of returns. In particular, the overall risk run to the point of closing the $i^{th}$ trade of trader $k$, $V_{ik}$, is defined as the variance of returns from their first trade to their $i^{th}$ trade:

$$V_{ik} = variance(R_{jk}), j \in [1, i].$$  

Sharpe ratio
The Sharpe ratio is used to measure the risk-adjusted investment performance in this study (Sharpe, 1998). The accumulated Sharpe ratio at the point of closing the $i^{th}$ trade of trader $k$, $S_{ik}$, is calculated as follows from their first to their $i^{th}$ trade:

$$S_{ik} = \frac{\text{mean}(R_{jk})}{\sqrt{\text{variance}(R_{jk})}}, \quad j \in [1, i].$$

**Control Variables**

As we are interested in the degree to which traders improve their trading performance through experience, we add behavioral variables to control for trader behavior, including holding time, investment size and trading frequency. Holding time is a unique concern for short-term trading markets, such as spread trading, as data from ordinary stock markets often do not cover both the purchase and sales related to all stocks held. Since short-term markets are highly volatile (Chordia et al., 2001), it is generally agreed that longer holding time leads to higher risk in spread trading market. Nicolosi et al. (2009) found that the size of a trader’s investment provides a good proxy for their level of confidence in their decision. In a similar fashion to Seru et al. (2010), who control for the number of trades in a specific period, we use three variables to control trading frequency from a variety of perspectives.

**Holding time**

Let $t'_{ik}$ represents the time when trader $k$ closes their $i^{th}$ trade. The holding time associated with the $i^{th}$ trade of trader $k$, $H_{ik}$, is defined as the number of seconds between the opening and closing of the $i^{th}$ trade:

$$H_{ik} = t'_{ik} - t_{ik}.$$

**Investment size**

The size of the investment of the $i^{th}$ trade of trader $k$, $ST_{ik}$, is defined as the amount of money invested in that ‘buy’ or ‘sell’ trade.

**Time after the previous trade**

The time period from the opening of the $(i-1)^{th}$ trade to the opening of the $i^{th}$ trade of trader $k$, $TAT_{ik}$, is defined as:

$$TAT_{ik} = t_{ik} - t_{i-1k}.$$

**The number of trades in seven days**
The number of trades in the seven-day period ending at \( t_{ik} \) for trader \( k \), is denoted \( TNS_{ik} \).

**Average number of trades per day**

The average trade number per day of the \( i^{th} \) trade of trader \( k \), \( ATN_{ik} \), is defined as the average number of trades per day placed by trader \( k \) during the period from \( t_{1k} \) to \( t_{ik} \). \( ATN_{ik} \) is calculated as follows:

\[
ATN_{ik} = \frac{i}{86400},
\]

where 86400 is the number of seconds in one day.

### 3.3 Analysis

#### 3.3.1 Linear Mixed Model

The spread trading data is essentially panel data, as each trader can place multiple trades. With panel data, the estimation of ordinary linear regression may be biased, and unobserved trader-specific characteristics, such as intelligence, risk attitude and professional knowledge might help explain how traders learn from experience (Cameron and Trivedi, 2005). To account for trader heterogeneity, we follow the approach suggested by Seru et al. (2010) and use the linear mixed model to control the unobserved trader-specific characteristics.

We follow Cnaan et al. (1997)’s suggestion and develop our model in two stages. We will let \( k = 1, \ldots, N \) index the traders in the spread trading data. Let \( Y \) represent the dependent variables, which will be returns, risk and Sharpe ratios, respectively. Let \( Z \) denote the trade level covariates, and we use

\[
Z = \begin{bmatrix} E \\ C \end{bmatrix},
\]

where \( E \) is experience and \( C \) includes those control variables mentioned in the previous section. The regression model of the first stage (trade level) is

\[
y_{ik} = z_{ik} \beta_k + e_{ik}, \quad k = 1, \ldots, N
\]
where $y_{ik}$ is the dependent variable (either returns, risk or Sharpe ratios) of the $i^{th}$ trade of trader $k$, $z_{ik}$ is the covariate vector of the $i^{th}$ trade of trader $k$, $e_{ik}$ are zero mean error terms and $\beta_k$ are the regression coefficients for trader $k$. In the second stage (trader level), $\beta_k$ are regarded as dependent variables, and the mean of the $\beta_k$ depends on trader level characteristics. Let $a_{E,k}'$ and $a_{C,k}'$ denote the vector of trader level characteristics affecting the coefficients of experience ($E$) and the control variables ($C$), respectively. We assume that both slope and intercepts of traders can vary, so we use

$$a_{E,k}' = (1, k),$$

where $k$ is used as the unique ID for each trader. The regression model is

$$\beta_k = A_k \alpha + b_k, \quad (2)$$

where

$$A_k = \begin{bmatrix} a_{E,k}' & 0 \\ 0 & a_{C,k}' \end{bmatrix}$$

$$\alpha' = (\alpha_{E}', \alpha_{C}').$$

And $\alpha_{E}'$ and $\alpha_{C}'$ are regression parameter vectors. Combining equation (1) and (2) we have

$$Y_k = Z_k \beta_k + e_k = Z_k A_k \alpha + Z_k b_k + e_k. \quad (3)$$

There are two types of regression parameters in equation (3). The $\alpha$'s are called fixed effects and help to test our hypotheses. On the other hand, the $b_k$'s, which are termed random effects, are independent random variable with zero mean and are often considered as error terms. We use the method proposed by Pinheiro et al. (2007) to estimate the regression coefficients, including both fixed effects and random effects.

### 3.3.2 Fixed Effect Regression Models

We estimate the fixed effect regression model, which is presented in equation (1), for three dependent variables respectively. First, we test Hypothesis 1 by regressing returns of trader $k$ on their experience. We, therefore, estimate the following regression:
$R_{ik} = \alpha + \beta E_{ik} + \beta^H H_{ik} + \beta^{ST} ST_{ik} + \beta^{TaT} TaT_{ik} + \beta^{TNS} TNS_{ik} + \beta^{ATN} ATN_{ik} + \epsilon_{ik}, \quad (4)$

where for trader $k$, $R_{ik}$ is the return of their $i^{th}$ trade, $E_{ik}$ is the measure of their experience at the opening of the $i^{th}$ trade, $H_{ik}$ is the holding time of their $i^{th}$ trade, $ST_{ik}$ is the investment size of their $i^{th}$ trade, $TaT_{ik}$ is the time period between their previous trade and their $i^{th}$ trade, $TNS_{ik}$ is the number of trades they placed in the seven days prior to the $i^{th}$ trade, and $ATN_{ik}$ is the average number of trades per day they executed from their first trade to the opening of their $i^{th}$ trade. We use $\epsilon_{ik}$ to denote the regression error term, and $\alpha, \beta, \beta^H, \beta^{ST}, \beta^{TaT}, \beta^{TNS}$ and $\beta^{ATN}$ are determined by parameter estimation.

Second, we test Hypothesis 2 by regressing the degree of risk taking by trader $k$ up to the closing of the $i^{th}$ trade on the experience of that trader up to that point. To achieve this we estimate the following regression:

$V_{ik} = \alpha + \beta E_{ik} + \beta^H H_{ik} + \beta^{ST} ST_{ik} + \beta^{TaT} TaT_{ik} + \beta^{TNS} TNS_{ik} + \beta^{ATN} ATN_{ik} + \epsilon_{ik}, \quad (5)$

where $V_{ik}$ is the volatility of returns associated with trader $k$’s $i^{th}$ trade.

Finally, we test Hypothesis 3 by regressing trader $k$’s Sharpe ratio up to the point of closing their $i^{th}$ trade on their experience up to that point. We, therefore, estimate the following regression:

$S_{ik} = \alpha + \beta E_{ik} + \beta^H H_{ik} + \beta^{ST} ST_{ik} + \beta^{TaT} TaT_{ik} + \beta^{TNS} TNS_{ik} + \beta^{ATN} ATN_{ik} + \epsilon_{ik}, \quad (6)$

where $S_{ik}$ is trader $k$’s accumulated Sharpe ratio up to the point of closing the $i^{th}$ trade.

### 3.3.3 Controlling Biases

There are two possible sources of biases which could affect our analysis. The first is the selection bias resulting from our Sharpe ratio calculation. In particular, we cannot calculate the Sharpe ratio for a trader’s first trade. Consequently, we exclude certain trades and may introduce bias. We follow Seru et al. (2010)’s approach and use Heckman two-stage method to control this bias (Heckman, 1976). The second potential bias is survivorship bias. It is possible that traders who learn to improve their performance through experience survive longer in the market and place more trades than those who do not learn. Consequently, analysis which does not control for survivorship bias may give misleading results. We observe the effect of
survivorship bias by comparing two groups with different survival periods. The details are discussed below.

### 3.3.3.1 Heckman Two-Stage Method

To control the selection bias we adopt Heckman (1976)'s two-stage method. This is widely used to handle sample selection problems in econometrics (Toomet and Henningsen, 2008).

The common sample selection problem is modeled as follows: the observation equation is given by:

\[ y_i = x_i'\beta + \varepsilon_i, \quad (7) \]

where \( y_i \) is the dependent variable, \( x_i \) are the regressors, \( \beta \) is the regression coefficient and \( \varepsilon \) is a normally distributed error term. However, the \( y_i \) of some observations (in our case some Sharp ratios) are missing, so a direct estimation with ordinary linear regression will be biased. Heckman (1976)'s solution consists of two stages. All observations are included in the first stage, and only the observations with \( y_i \) not missing are selected to the second stage. The first stage regression is used to predict selection:

\[ z_i^* = w_i'r + u_i, \quad (8) \]

where \( z_i^* \) is 1 if the \( i^{th} \) observation is selected, otherwise 0, \( w_i' \) are the regressors, \( r \) is the regression coefficient and \( \varepsilon \) and \( u \) are error terms and assumed to follow a bivariate normal distribution:

\[
\begin{pmatrix}
\varepsilon \\
u
\end{pmatrix}
\sim N
\begin{pmatrix}
0 \\
0
\end{pmatrix},
\begin{pmatrix}
1 & \rho \\
\rho & \sigma^2
\end{pmatrix}
\]

According to Toomet and Henningsen(2008)the observation equation can be re-written as follows:

\[ y_i = x_i'\beta + \varepsilon_i = x_i'\beta + E[\varepsilon_i|z_i^* > 0] + \eta_i = x_i'\beta + E[\varepsilon_i|u_i > -w_i'r] + \eta_i \]

\[ \equiv x_i'\beta + \rho\sigma \lambda(w_i'r) + \eta_i \quad (9) \]

where \( \lambda(\alpha) = \varphi(\alpha)/\Phi(\alpha) \) is commonly termed the inverse Mill's ratio, \( \varphi(\alpha) \) and \( \Phi(\alpha) \) are standard normal density and cumulative distribution functions and \( \eta \) is an independent disturbance term. The multiplicator \( \rho\sigma \) is unknown and can be estimated.
by the ordinary least-squares method (OLS). The selection bias can be adjusted by including the inverse Mill’s ratio in the second stage (Heckman, 1976).

We develop our model in a setting similar to Serafino et al. (2010): a trade is selected if this is not a trader’s first trade, and the Sharpe ratio is calculated and assigned to the trade. The selection condition comes from the fact that we cannot calculate the Sharpe ratio by definition if only one trade is placed. In the first stage, the independent variables are

$$w' = (E, APo, APr),$$

where $E$ is the experience measure, $APo$ and $APr$ are the accumulated points and profit of the trader at the time the trade is placed, respectively.

### 3.3.3.2 Traders Surviving Shorter/Longer

To control survivorship bias, which results from that traders with poor performance cease trading, Nicolosi et al. (2009) examined whether experience results in performance improvement by using only the traders who trade in both the first and the second half of the period covered by their data. However, with this approach, traders with short active periods may be selected. For example, a trader is selected by this above approach if he starts trading from the end of the first half period and stops in the beginning of the second half period, even though the active period is relatively short.

To avoid this scenario and to take account of trader-specific characteristics, we adopt a different approach. In particular, we split all traders into two groups: those that stay active in the spread-trading market for shorter and longer periods. We define a trader’s active period as the time from their first trade to the last of their trades in the dataset. On this basis, we find that the median of a trader’s active period is 185 days. Consequently, we split traders into those that have active periods shorter and greater than or equal to 180 days. We then run linear mixed models with dependent variables of returns, volatility of returns and Sharpe ratios (see equations (4), (5) and (6)) for both groups of traders, separately.
4 RESULTS

4.1 COMPARING LEARNING IN TERMS OF RETURN, VOLATILITY AND RISK-ADJUSTED PERFORMANCE

The results of estimating the linear mixed models using equations (4), (5) and (6) are presented in Table 2. Overall these results show that with more experience traders make higher returns but take greater risks and achieve lower Sharpe ratios. In particular, the coefficient of experience (0.1068, p < 0.001) in equation (4) shows that there is a significant positive relationship between return and experience. This result supports our first hypothesis. The regression coefficient in equation (5) is 118.3354 (p < 0.001) and supports our second hypothesis that traders take greater risk having gained more experience. The significant negative regression coefficient in the regression between experience and Sharpe ratio (-0.01077, p < 0.001) does not support hypothesis 3 and in fact suggests that traders’ risk-adjusted performance declines as a result of experience.

Our finding that traders with more experience get higher returns is consistent with the previous studies (Feng and Seasholes, 2005; Nicolosi et al., 2009; Seru et al., 2010), and these earlier studies have argued that these improved returns are evidence that traders can learn from experience. However, we find that traders take higher risks while making higher profit, and the resulting risk-adjusted performance, which is assessed by Sharpe ratio, declines. Thus, our results suggest that traders do not learn to improve risk-adjusted performance.
### Table 2 Result of Linear Mixed Model

<table>
<thead>
<tr>
<th></th>
<th>Return</th>
<th>Risk</th>
<th>Sharpe Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience</td>
<td>0.1068 ***</td>
<td>118.3354 ***</td>
<td>-0.01077 ***</td>
</tr>
<tr>
<td><strong>Controls</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Holding Time</td>
<td>-1.9707 ****</td>
<td>41.66083 ***</td>
<td>-0.000064 **</td>
</tr>
<tr>
<td>Investment Size</td>
<td>-0.01508 ***</td>
<td>-0.40062 **</td>
<td>0.000262 ***</td>
</tr>
<tr>
<td>Time after Previous Trade</td>
<td>0.191521 ***</td>
<td>18.39314 ***</td>
<td>-0.00055 ***</td>
</tr>
<tr>
<td>Trade Number in 7 Days</td>
<td>-0.00151 ***</td>
<td>0.244506 ***</td>
<td>0.0000171 ***</td>
</tr>
<tr>
<td>Average Trade Number per Day</td>
<td>0.000138 **</td>
<td>-0.0229 **</td>
<td>0.0000042 ***</td>
</tr>
</tbody>
</table>

***,**,* Significant at the 0.1%, 1% and 5% levels, respectively.

#### 4.2 Result of Controlling for Potential Bias

**Selection Bias: Heckman Two-Stage Method**

The results of conducting the Heckman two-stage method are presented in Table 3. The selection bias is shown to be a legitimate concern because \( \rho > 0 \), indicating that the unobserved values tend to be lower than those which are observed. After controlling for selection bias in the second stage, we can see that experience is negatively related with Sharpe ratio (-0.00755, \( p < 0.001 \)). Although the magnitude of the coefficient is smaller than that estimated in the earlier analysis, it still remains negative and significant, confirming that lower Sharpe ratios are generally obtained by traders with greater experience.
Table 3 Result of Heckman Two-Stage Method

<table>
<thead>
<tr>
<th>First Stage Selected InSample</th>
<th>Second Stage Sharpe Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experience</td>
<td>0.26***</td>
</tr>
<tr>
<td>Accumulated Profit</td>
<td>-0.00000067</td>
</tr>
<tr>
<td>Accumulated Point</td>
<td>-0.0000007</td>
</tr>
<tr>
<td>Holding Time</td>
<td></td>
</tr>
<tr>
<td>Investment Size</td>
<td></td>
</tr>
<tr>
<td>Time after Previous Trade</td>
<td></td>
</tr>
<tr>
<td>Trade Number in 7 Days</td>
<td></td>
</tr>
<tr>
<td>Average Trade Number per Day</td>
<td></td>
</tr>
<tr>
<td>Inverse Mills Ratio</td>
<td>0.04402*</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>0.4941</td>
</tr>
<tr>
<td>( \rho )</td>
<td>0.08909</td>
</tr>
</tbody>
</table>

***, **, * Significant at the 0.1%, 1% and 5% levels, respectively.

Survival Bias

The results of estimating the linear mixed models using equations (4), (5) and (6) for the trades of those that have active trading periods (a) shorter and (b) greater than or equal to 180 days are presented in Table 4. For the group of traders with shorter active trading periods, return is negatively related with experience (-0.31824, \( p < 0.001 \)), risk is positively related with experience (74.90419, \( p < 0.001 \)) and Sharpe ratio is negatively related with experience (-0.0273, \( p < 0.001 \)). Consequently, our results suggest that this group make lower profits, take higher risk and, accordingly, have lower Sharpe ratios as they gain experience. It is perhaps not surprising that those traders who remain active for a shorter period make lower returns as they gain experience, because there is little incentive for this group to continue trading. They also appear to take greater risk while accumulating experience, and this results in them achieving lower Sharpe ratios.
On the other hand, for traders with longer active trading periods we find that return is positively related with experience (0.072847, p < 0.001), risk is positively related with experience (123.6343, p < 0.001), and the Sharpe ratio is negatively related with experience (-0.00854, p < 0.001). Consequently, these traders tend to make higher returns, take greater risk and achieve lower Sharpe ratios as they gain experience. It is important to notice that both groups of traders take higher risk and achieve lower Sharpe ratios as they gain more experience. This implies that even those individuals who have the longer active trading periods fail to control their risk the more they trade and this results in worse risk-adjusted performance. Consequently, these results, after controlling for survival bias, still lead us to reject hypothesis 3.

Table 4 Comparison between Traders surviving Shorter and Longer

<table>
<thead>
<tr>
<th></th>
<th>Return</th>
<th>Risk</th>
<th>Sharpe Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Surviving Shorter</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experience</td>
<td>-0.31824 ***</td>
<td>74.90419 ***</td>
<td>-0.0273 ***</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Holding Time</td>
<td>-2.0823 ***</td>
<td>69.38292 ***</td>
<td>-0.00538 ***</td>
</tr>
<tr>
<td>Investment Size</td>
<td>-0.01922 ***</td>
<td>-0.06389 **</td>
<td>0.000174 **</td>
</tr>
<tr>
<td>Time after Previous Trade</td>
<td>0.160054 ***</td>
<td>19.07984 ***</td>
<td>0.000003</td>
</tr>
<tr>
<td>Trade Number in 7 Days</td>
<td>-0.00012 **</td>
<td>-0.03906 **</td>
<td>0.00002 ***</td>
</tr>
<tr>
<td>Average Trade Number per Day</td>
<td>0.00007</td>
<td>0.002163</td>
<td>0.0000003 **</td>
</tr>
<tr>
<td><strong>Surviving Longer</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experience</td>
<td>0.072847 ***</td>
<td>123.6343 ***</td>
<td>-0.00854 ***</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Holding Time</td>
<td>-1.97785 ***</td>
<td>40.43433 ***</td>
<td>0.000382 ***</td>
</tr>
<tr>
<td>Investment Size</td>
<td>-0.01536 ***</td>
<td>-0.4378 **</td>
<td>0.000277 **</td>
</tr>
<tr>
<td>Time after Previous Trade</td>
<td>0.199023 ***</td>
<td>18.782 ***</td>
<td>-0.00076 ***</td>
</tr>
<tr>
<td>Trade Number in 7 Days</td>
<td>-0.00198 ***</td>
<td>0.355005 ***</td>
<td>0.000017</td>
</tr>
<tr>
<td>Average Trade Number per Day</td>
<td>-0.00013 **</td>
<td>-0.07509 **</td>
<td>0.000003</td>
</tr>
</tbody>
</table>

***, **, * Significant at the 0.1%, 1% and 5% levels, respectively.
5 Discussion

Our results concerning the impact of trading experience on returns are consistent with the extant literature, namely that traders make higher returns as they gain more experience (Feng and Seasholes, 2005; Nicolosi et al., 2009; Seru et al., 2010). Earlier studies have regarded this as the evidence that traders learn to improve their performance. However, importantly, our results also show that these higher returns are at the expense of higher risk and that this additional risk causes risk-adjusted performance to decline.

Chiang et al. (2011) regard decreasing returns as the evidence of naïve reinforcement learning, namely traders repeating those actions which produced greater returns in the past. However, such an approach fails to take account of the fact that that higher returns may be obtained at the expense of higher volatility (Fama and MacBeth, 1973; Glosten et al., 1993). It might therefore be argued that these individuals are just reinforced by risk-taking behavior accompanied with high return and high volatility. By contrast, individuals who employ Bayesian learning can appropriately update probability estimates conditioned on new information. As a result they can improve their decision choices, thus enabling them to not only increase returns but also to improve their risk-adjusted performance.

Our results indicate that traders' risk-adjusted performance decreases the longer they trade. This result suggests that traders are more subject to reinforcement learning than Bayesian learning. In particular, individuals may try trading several strategies with different levels of risk. Since higher risk generally brings both higher profits and greater losses, traders who undertake riskier strategies will either make higher profit or suffer greater losses. Those traders making higher profit are reinforced by the riskier strategies, while those suffering higher losses are likely to quit the market. This is the pattern we observe and results in those traders with greater experience generally taking greater risk.
6 Conclusion

We analyze 8,441,805 trades from 28,061 spread traders over a 10 year period. We find that traders make higher returns as they gain more experience, which is consistent with the findings of Seru et al. (2010), Feng and Seasholes (2005) and Nicolosi et al. (2009). However, our results also show that traders take greater risk with accumulating experience, resulting in lower risk-adjusted performance. It appears therefore that traders only improve returns by taking greater risk. The results are consistent with traders’ risk-taking behavior being reinforced by the accompanying higher returns. This leads them to take greater and greater risk without full understanding of the degree of risk they are taking. This conclusion still holds after we take selection bias and survivorship bias into account.

This, to our best knowledge, is the first study to examine the effects of learning through experience on traders in real world financial markets, taking account of their volatility of returns and risk-adjusted performance. The results lead us to question one of the rational assumptions underlying the neoclassical approach, namely that individuals learn, following the Bayesian rule i.e. they appropriately update prior probability estimations conditional on new information or events. Rather, our results suggest that traders learn by reinforcement, choosing strategies which led to ‘better’ outcomes in the past. It appears that in adopting this approach, traders may overweight the value of returns in assessing what are the ‘better’ outcomes and this leads them to under-assess the underlying risk. If the results we obtain are mirrored in future studies examining the effects of learning on risk adjusted performance in other financial markets, they have important implications for the efficiency of financial markets. In particular, they suggest that it is unlikely that individual traders will learn the lessons of excessive risk-taking from previous periods of excessive exuberance in financial markets which led to bubbles and eventual crashes. As a result, our findings point to the need for intervention by government or financial authorities to adopt measures which make clearer the risk involved in particular assets or investment strategies and/or to provide incentives for traders to focus more on risk-adjusted performance.
7 Reference


