Do retail FX traders learn?*

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Abstract

We investigate the actions of retail foreign exchange traders in order to understand whether they are learning either how to trade better or about their innate abilities as traders. We use a unique database that details at a daily frequency all actions of a sample of traders using a leading retail FX platform. We find that retail FX traders do act as though they are learning from their trading experiences - they are more likely to cease to trade and to trade both smaller volumes and less frequently following unsuccessful trades. These effects are stronger for younger and less experienced traders who might be expected to have more to learn than older, more experienced traders. However, the performance of even very experienced traders is not particularly good, with most consistently losing money. We estimate a small but statistically significant deterioration in performance with experience once we have accounted for the endogenous decision to cease trading. Our results are consistent with irrational learning where traders interpret signals about their abilities in overly positive ways, adapting their trading strategies but in doing so taking on inappropriate trades and so making increasing losses. We interpret this as traders learning to fail due to non-rational learning.

Keywords: Market microstructure; foreign exchange; retail trading; learning

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1 Introduction

We address the issue of how traders learn using a new database from one of the fastest growing sectors of financial markets, retail foreign exchange trading. Historically, foreign exchange (FX) trading has been the preserve of large institutions largely due to the enormous costs of trading FX at the retail level. The Bank for International Settlements viewed retail FX trading as negligible in 2001. However, advances in technology, combined with the consensus that FX markets are both liquid and have low correlations with other markets, has led to the establishment of numerous platforms offering even very small retail investors relatively cheap access to FX markets. By 2010, trading in the retail segment of the FX market was estimated to be $125-150 billion per day, equivalent to 8-10 percent of global spot turnover (King and Rime (2010)).

We use data from one such retail trading platform that details daily activity levels of over ninety-five thousand individual investors over a thirty month period to investigate how individual traders learn about FX trading and how this affects their decisions to trade. The retail trading sector of the foreign exchange market is in the spotlight after the French financial markets regulator, the Autorité des Marchés Financiers (AMF), released results of a study[1] concluding that 89% of particpants examined lost money, and that even active and regular retail investors saw their losses mount suggesting that "individual investors learn little over time." Natalie Lemaire of the AMF's Retail Investor Relations Directorate went so far as to say that "Foreign exchange trading is a market that individual investors should avoid."

The literature has identified two specific ways in which financial market participants might learn. The first, classical, approach is through "learning by doing" whereby traders improve their ability as they trade (Arrow (1962); Grossman, Kihlstrom, and Mirman (1977)). This appears to be the type of learning AMF had in mind. An alternative is that traders learn about their inherent and largely fixed level of ability (Mahani and Bernhardt (2007); Linnainmaa (2011)). If they infer from trading that they have skill, they will continue to trade. Conversely if they infer a low level of ability they cease trading. As discussed further below, any learning may or may not be rational.

[1] AMF press release, 13 October 2014. See www.amf-france.org

In learning by doing models, traders learn how to trade by trading.[2] This could be through acquiring better trading skills or by learning to avoid trading errors, including behavioural biases such as the disposition effect. This way of learning leads traders to alter their strategies through time in response to performance signals but, crucially, suggests that performance should improve with experience, though potentially at a decreasing rate. Empirical evidence in support of a considerable "learning by doing" effect is presented in Feng and Seasholes (2005) and Dhar and Zhu (2006). These papers suggest that traders learn through experience not to exhibit the disposition effect behavioural bias and that this drives their performance improvement over time. Kaustia, Alho, and Puttonen (2008) report that experienced investors seem less prone to anchoring effects than novice investors. Nicolosi, Peng, and Zhu (2009) show that individuals exhibit considerable improvement in performance as their experience grows (a risk-adjusted portfolio return increase of around 2% per year). Similarly, Barrot, Kaniel, and Sraer (2014) show that experienced equity retail traders trade faster than less experienced traders and outperform as a result, suggesting they have learned better trading skills.

In rational learning about abilities models, traders initially do not know how good they are at trading. They trade to learn about their innate abilities, knowing that the population is heterogeneous with some traders being skilled and some unskilled.[3] Traders behave as Bayesian updaters, learning from their trading histories and changing behaviour accordingly. Once a trader receives a strong enough set of signals that she lacks trading skills she ceases trading. A trader receiving positive signals continues to trade and should increase trading activity. As traders gain experience their sensitivity to new performance signals declines. Long-lived traders should perform well as these are the traders that have learned that they have skills. Linnainmaa (2011) presents a rational learning model whereby investors actively trade to learn about their abilities. One important implication of his model is that if an individual places a high enough value on observing another signal about her ability she will trade even though she rationally expects to lose money. Since she expects to lose money she only trades small amounts. If she receives a positive signal through making a successful trade, she infers skill and subsequently trades more. If she makes a losing trade she infers a lower level of skill and trades less. Eventually, if

[2]Dhar and Zhu (2006), Nicolosi, Peng, and Zhu (2009) and Seru, Shumway, and Stoffman (2010).
[3]Linnainmaa (2011) and Mahani and Bernhardt (2007).

an investor receives enough negative signals she may cease trading entirely. The impact of additional signals of ability is largest at the start of a trader's career and for traders with diffuse priors. The incremental effect of a positive signal on the decision to continue trading or on the scale of trades declines with experience.

The predictions of alternative non-rational learning models are very similar. In these models traders may again trade to learn. However, their learning is biased by one or more behavioural tendencies - including overconfidence or attribution bias - and so even poorly performing traders continue to trade.[4] Chiang, Hirshleifer, Qian, and Sherman (2011) consider irrational investors subject to naive reinforcement learning. Here, investors expect the returns that they have personally experienced to recur even when this expectation is unjustified. Experiencing a trading success then leads them to expect future trading success - the same tendency as a rational Bayesian learner - however naive reinforcement learners overweight their personal experience and so do not update their beliefs optimally. Gervais and Odean (2001) describe how another behavioural bias - overconfidence - can also lead investors to make mistakes as they gain experience. They model the process by which individuals learn to be overconfident about their trading abilities. A positive signal leads a trader to update her belief about her skills. However, attribution bias leads her to do so to an inappropriate extent, overweighting the probability that success is due to superior ability and under-weighting alternative explanations such as luck. Conversely, unsuccessful trades are deemed due to external forces to too great an extent. In Gervais and Odean's model investors do not start out overconfident. However, overconfidence increases over initial trading periods before declining. As she ages, an investor develops a more realistic assessment of her abilities. But while she is overconfident she behaves sub-optimally, trading too aggressively which lowers her expected profits. In these non-rational models even experienced traders still perform badly and performance may initially deteriorate with experience. It is, however, anticipated that performance finally improves as rational updating prevails.[5]

This is the crucial difference between the rational and non-rational approaches to learning. In a rational model, expected returns increase with experience, either because traders

[4] Odean (1998), Gervais and Odean (2001), Barber, Lee, Liu, and Odean (2011), Chiang, Hirshleifer, Qian, and Sherman (2011).

[5] List (2003), Agarwal, Driscoll, Gabaix, and Laibson (2008) and Kaustia, Alho, and Puttonen (2008).

have "learned by doing" how to trade better or because traders have learned about their abilities by trading and only the good remain active. Conversely, expected returns decline with experience for non-rational models, at least until investors have learned to avoid behavioural biases.

Most of the empirical work on learning in financial markets has used data from equity markets, often considering the market equity trades of Finnish or Taiwanese investors.[6] We add to our understanding of learning in financial markets by considering, for the first time, data from the foreign exchange market. This comes with the added advantage, relative to secondary market equity data, of not having to separate active trades from long-term passive investments. Due to the nature of the trading architecture used, we are confident that the overwhelming majority of the trades in our database are active.

We first test for cross sectional heterogeneity in trading ability. If traders trade in order to learn whether they are skilled or not then at least some retail traders must demonstrate skill. If no individual trader is skilled then each individual knows that they are not skilled and hence would not trade. The learning by doing explanation relies on traders being able to improve their performance over time through the act of trading. Again, this would imply that some traders are better than others. Anticipating our results, we find very strong evidence of cross-sectional heterogeneity in trading ability supporting the basic premises of the competing learning models.

Second, we test whether the decision to cease trading is related to performance. If traders learn about their innate abilities by trading then their performance each day will give them a signal. If the learning about ability explanations are correct we would expect these signals to influence the decision of an individual whether to continue trading or not. We also test whether the sensitivity to performance signals are highest for traders we expect to have the most to learn (e.g. novice traders or younger traders with less life experience).

Third, and closely related to the decision to quit, we test whether traders receiving positive signals about their abilities alter their trading activities. As traders learn, either about their innate abilities or how to trade, a positive signal makes subsequent trading

[6] Finland: Seru, Shumway, and Stoffman (2010); Linnainmaa (2011). Taiwan: Chiang, Hirshleifer, Qian, and Sherman (2011); Barber, Lee, Liu, and Odean (2011).

more attractive. Hence we expect traders to trade in greater volume or more frequently following a profitable trading day. Again, our results strongly support the hypotheses that traders learn from their performance. The decision to quit trading is strongly negatively correlated with both performance on the previous trading day and career trading performance. The sensitivity of the quit decision to performance declines with experience and age, consistent with learning effects being stronger for traders with the most to learn. Finally, traders also change their trading behaviour following success. Trade size increases and the gap between trades decreases following good performance. However, there are some aspects of the relationship between trading signals and subsequent trading decisions that are hard to reconcile with purely rational learning. For example, while there is a generally positive relationship between the dollar amount earned on da t and the probability of an increased trade volume on day $t+1$, this is actually strongest in the immediate vicinity of breaking even. That is, both tiny gains or losses predict increased future trading volume much more strongly than do larger gains. Further, there is a clear discontinuity at zero with tiny gains increasing the probability of increased future trading volume much more than tiny losses. Since there is essentially no meaningful difference between losing a few cents and making a few cents, the significant difference in the reaction to these two equivalent signals about ability is suggestive of behavioural biases being present.

The final set of tests are specifically designed to discriminate between learning models. The tests examine whether performance is related to experience. The learning by doing and rational learning about ability models both suggest performance should improve with experience. In its pure form, the rational learning about ability model assumes that a given traders' ability is fixed. Performance improves with experience in the population because unskilled traders cease trading and only skilled traders remain. That is, performance improves because of the endogenous decision to quit in a heterogeneous population. Once this is accounted for, performance should not be related to experience. The learning by doing model predicts a positive relationship between performance and experience even after the endogenous decision to quit is taken into account. Traders that remain in the sample get better at trading with experience (i.e. ability is not fixed). The irrational learning alternative suggests that performance may instead deteriorate with experience. Even correcting for the quit decision, the performance of traders that remain active may initially worsen with experience as their behavioural biases lead them to "learn to fail".

Analysing the relationship between performance and experience is complicated in the presence of heterogeneity and endogenous quit decisions. We use a Heckman-style approach that corrects for cross sectional heterogeneity and selection biases. Both of these corrections have significant impacts on our estimates of the experience-performance relationship. Once they are taken into account our finding is that performance deteriorates with experience consistent with the non-rational learning model. The magnitude of these effects is not large and a trader with 100 days of active trading experience - large in terms of our sample - is only 5.8% less likely to have a winning month than a complete novice.

Overall, retail FX traders appear to learn in two main ways. First, they learn about their innate skills by trading and are more likely to trade less or even cease trading after bad performance signals. The sensitivity of trading decisions to negative signals is much larger for traders that are likely to be learning the most (novice traders and younger traders). These effects are statistically significant and economically large. While broadly consistent with rational learning, there are also elements of non-rational inference in these results. Second, after accounting for these learning about ability effects, a small amount of non-rational learning remains. Trader performance deteriorates with experience and this explains why even relatively long-lived traders who might otherwise be expected to have learned that they have skill and/or learned how to trade still do not perform particularly well.

The rest of the paper proceeds as follows. The next section describes our data set, section 3 details our statistical analysis and we conclude in section 4.

2 Data

2.1 Data source

The data used in this paper come from an on-line retail foreign exchange trading platform that wishes to remain anonymous. The data are in two files, a trading database and a trader characteristics database. The two databases can be linked through unique trader identification codes.

The trading database contains daily records of the complete trading history of a random sample of traders using the platform. All trading is for real money. The data provider does offer paper trading facilities to customers but these are not included in our data. The platform is continually active Monday through Friday but trading is not possible on weekends. Mark-to-market reconciliation takes place at 9pm GMT time each day. The platform allows for trading in all the major currencies primarily in the spot market although a small number of cash-for-difference trades are included in the data. The data provider informs us that the large majority of trades are in euro-dollar spot. Traders may use the usual range of market orders, limit orders, stop loss and take profit orders.

Each trader-day entry gives:

1. Number of trades made
2. Total value of trades (USD)
3. Total value of open positions (USD)
4. Profit/loss, realised and marked-to-market as appropriate, after trading costs[7]
5. Capital injections and extractions (USD)

The trader characteristics file contains the following information:

1. Age of trader
2. Location of trader by country
3. Location of trader by city (for some countries)

Details of individual trades are not available, only the daily aggregates. Only the US dollar equivalent of open overnight positions is disclosed. We do not know the currencies of any overnight positions or the direction of any exposures.

While the trader location fields indicate that traders are located in 98 different countries, the client base is extremely focused. Only four countries have more than one percent of

[7] Spreads are relatively narrow in this market. The data provider reports a typical spread of 1.9 pips in dollar-euro, 1.8 pips in yen-dollar and 2.7 pips in dollar-sterling.

the client base and two countries between them have 89% of traders. City information is only provided for some countries, but fortunately these include the main ones where our data provider's clients reside.

The data begin on 4 January 2010 and end on 29 June 2012. The data provider gave us the complete trading history of a random sample of 95,617 unique traders, amounting to almost 4.8 million trader-day entries. Since this is a new database and information at such fine detail on retail trading is scarce we present detailed descriptive statistics in the following subsection. For confidentiality reasons, however, we cannot disclose certain statistics.

A new trader can be identified by the placing of an initial deposit into his or her trading account.[8] Traders typically start trading very soon after this deposit is made, often on the same day. Some ten percent of our sample of traders commenced trading before our data begin and so our data are left censored. In the majority of the analysis below such traders are included in the sample. For the survival analysis, however, these traders are removed from the sample (and right censoring where traders have not stopped trading within the sample is accounted for in the analysis).

A trader is deemed to have ceased trading if his last observed active day is more than one month before the end of the sample. The mean interval between trading days is just four days in the sample and the median is one day. Just two percent of intervals exceed one month and so we are confident that a one-month cut-off should eliminate most misidentified exits. Our results are very robust to alternative cut-offs.[9]

We define a trader to be "trading" on a particular day if the number of trades made on that day is non-zero. We define a trader to be "active" on a given day if he either trades on that day or has an open position that day.

[8] We only have gender identification for a small proportion of traders but the overwhelming majority are male and so for ease we will identify traders as masculine in the rest of the paper.

[9] It is possible that traders join our data provider's network after trading elsewhere, or that traders leave the network to trade elsewhere. In these cases we would mismeasure their experience and lifespans which would add noise to our analysis.

2.2 Descriptive Statistics

Table 1 shows that the mean (median) trader in the sample is active on 45 (20) days. There is large variation in this number across traders, however, and the top quarter are active on at least 51 days, the top ten percent are active on at least 115 days and the top 5% are active on over 182 days. Conversely, the bottom quartile trade on fewer then eight days. The large number of relatively inactive traders is in common with related databases. Hieronymus (1977) states that over one-third of futures trading accounts were traded only a few times and Linnainmaa (2011) shows that the lower quarter of Finnish short-term equity traders only make two trades.

< Table 1 about here >

The median trader's average daily trading volume is approximately $41,000 and the median number of average trades per day is 7 (one round-trip counts as two trades).[10] The distribution of trading volume is extremely skewed and widely dispersed. More than one-quarter of traders have an average daily volume in excess of $100,000 and more than 5% trade in excess of $0.5 million per active day on average. The distribution of the average number of trades per day is much tighter. Ninety-five percent of traders make fewer than 25 trades per day on average.

The median trader has a success ratio (percentage of profitable days) of 50%. The mean is slightly lower. Again, the dispersion of success rates is high. More than five percent of traders lose money every day they trade. At the other end of the distribution, ten percent of traders gain on at least three out of every four active days.

The median trader loses $5.56 on average each active day (plus the opportunity cost of capital which we ignore). The distribution is left skewed and the average trader's average loss is much larger.[11] The overwhelming majority of our traders cannot live off the proceeds of trading since the average daily profit of even the trader at the 99th percentile is measured in just tens of dollars. Conversely, the lowest few percentiles are losing upwards of several hundred dollars per day, on average. Our traders are therefore likely to be similar to Mahani and Bernhardt (2007)'s prototypical novice speculator,

[10] We use medians rather than mean values in this section for confidentiality reasons.
[11] We cannot divulge exact values in this section of the paper for confidentiality reasons.

Kiyoshi Wakino, and pursue trading alongside a regular job rather than trading to make a living.

Losing money on average is another typical finding in retail trading markets. Linnainmaa (2011), for example, reports that the median Finnish active equity trader makes a loss of 21 euros per trade on average. As such, it appears that the level of trading in the foreign exchange market by retail customers is excessive. However, if individuals are uncertain about their trading abilities they can learn by trading. If the value of learning through making a trade exceeds his expected loss on that trade then it makes sense for an individual to trade 'too much'.

We do not report percentage returns in Table 1 due to data limitations. The database reveals the number and value of trades made on a day and any profit or loss made on that day (realised or marked-to-market). However, we cannot map profits or losses to individual trades. Dividing profit by traded volume at a daily frequency results in extreme values, not least because of instances where marked to market profits may occur on days without without trades. Similarly, dividing profits by the capital value of the account yields extreme values when capital values are low. In reality, the capital supporting these trades is in the bank accounts of traders rather than in their account with the trading platform. For these reasons we do not use returns in analysis performed at the daily frequency, and focus instead on success ratios. In the final part of the paper we move to a monthly frequency. Here we do use a proxy for returns (Ret) calculated as the total cumulated profits over a month divided by the total volume traded during the month. This proxy has more reasonable properties, though is still subject to a few huge outliers which we address through winsorisation. We also continue to use a monthly version of the success ratio in parallel with Ret and our results from these two proxies for performance are comparable.

3 Analysis

3.1 Cross sectional heterogeneity in trading ability

If traders trade in order to learn whether they are skilled or not then at least some retail traders must demonstrate skill. If no individual trader is skilled then each individual knows that they are not skilled and hence would not trade. Learning by doing implies that traders are able to improve their performance through the act of trading and this implies that some traders are better than others.[12]

We test for cross sectional heterogeneity by regressing the ith-trading day success dummy on the career success rate over all previous trades. We augment the regression with monthly fixed effects and dummy variables capturing the number of days experience each trader has. If no differences in performance exist or if any differences are merely transitory then the coefficient on career success rate will be zero. Systematic outperformance by some traders will result in a positive coefficient.

The results presented in Table 2 indicate that some traders systematically outperform others. The coefficient on career success rate is statistically and economically significant in each variant of the regression. In the benchmark regression (column 3) a trader with a perfect career success rate to date has a 0.43 higher probability of another success relative to an investor with no past successes.

< Table 2 about here >

We also split the data into investors' first (N<=10), early (10<N<=25), intermediate (25<N<=50) and late (N>50) trades. The coefficients are positive and significant in each sub-sample, and grow larger as we consider traders' successively later trades. The estimated coefficient increases for later trades since the career success rate become more precisely estimated as the number of observations per trader increases. The final row of the table gives the standard deviation of the career success rate and shows that it falls as

[12] Barber, Lee, Liu, and Odean (2014) show that around 1,000 Taiwanese equity day-traders are able to earn predictable abnormal returns net of fees out of a population of 360,000 day-traders. Linnainmaa (2011) demonstrates considerable cross-sectional heterogeneity in the performance of frequent retail traders in the Finnish equity market, as do Barrot, Kaniel, and Sraer (2014) in their analysis of French retail traders.

we consider later career trades. Nevertheless, the net effect is that heterogeneity persists, and actually increases, as we consider successively later career trades. A one standard deviation increase to average career success rates increases today's probability of success by 5.5% in the first trades sample, 7.4% for early trades, 8.5% for intermediate trades and 10.1% for late trades. Without conditioning on experience, a one standard deviation shock to career success rates increases today's probability of success by 7.5%.

These results show that there is clear cross sectional heterogeneity in the performance of our traders.[13] It is therefore reasonable that traders may participate in this market in order to learn about their own ex ante unobservable abilities. It is also possible that some traders are better than others because the former group has learned how to trade better, consistent with the learning by doing approach.

3.2 The decision to quit

The implications of the learning about ability class of models are that following a positive signal a trader will (a) continue to trade since he infers skill and (b) increase his level of activity (frequency of trading and/or size of positions). Activity levels increase since exploratory trades, where a trader expects to lose but is willing to pay to learn about their skill level, are likely to be very small to minimise the cost of learning. As he becomes more confident in his ability - and in the non-rational models he may become overconfident of his ability - he increases his activity level in the expectation of positive returns. Conversely, if a loss is made then the trader infers less skill and will trade less. Traders with a poor performance record will eventually infer that they are unskilled and, since trading is costly for them, will quit.

In this section we consider the decision to quit. We model this decision using a Cox proportional hazard rate model. Cox regressions model how different outcomes affect the hazard rate without the need to estimate or specify the baseline hazard. We include two main variables in the regression, the most recent trading day success dummy and the career success rate over all previous trades. We expect both variables to exert negative influence over the decision to quit since a success on the most recent trading day or a

[13] In section 3.4 we also demonstrate that a small proportion of our sample of traders has persistent abilities to earn profits

higher than benchmark career success rate should encourage a trader to continue as they are positive signals of his ability.

The basic model estimated is:

$$h(t|x) = h_0(t)exp(a + b_1 Day(t)Success + b_2 CareerSuccessRate + Controls) \quad (1)$$

where $h_0(t)$ is the unspecified baseline hazard.

< Table 3 about here >

The estimates reported in Table 3 suggest that the decision to quit is significantly influenced by performance of the most recent trading day and on career performance. A profit on the most recent trading day reduces the hazard rate by 31% relative to the baseline level of a loss-making day. That is, a trader is much less likely to quit trading tomorrow if he has made a profit from trading today. Similarly, the career success rate exerts a negative influence - the better the career success rate, the less likely it is that the trader will quit. Control variables such as the log of cumulative trading volume or number of trades, and month-year dummy variables are typically significant but their inclusion does not affect the key coefficients.

In learning about ability models, the sensitivity of the quit decision to success on the most recent trading day should be time-varying. Specifically, a novice trader learns a lot from the results of a day of trading and so the sensitivity of the decision to quit to success on that day is high. Conversely, an experienced trader with a longer history of trading learns less from an extra day of trading and so his quit decision is less sensitive to one day's performance. We follow Linnainmaa (2011) and perform a series of cross-sectional linear regressions. The dependent variable is an indicator dummy that takes the value one if the trader ceases trading after the current trade, and zero if he continues trading. The explanatory variable is the current trade success indicator dummy. Following the results of the Cox model above, this coefficient is expected to be negative as success should reduce the probability of quitting. The magnitude of the slope gives the sensitivity of the decision to quit to the information gleaned from the day's experience. We first run the regression for all traders active for their first trading day. The regression is then run for trader's second active day and another slope estimate is recorded. The process is continued up until the 50th active day.

Figure 1 plots the evolution of this slope coefficient. The plot reveals the expected path. The sensitivity of the quit decision to a successful trade is always significantly negative but the sensitivity is much greater in the early days of a trader's career. A positive signal regarding the trader's ability in the form of a successful trading day reduces the likelihood that the trader will cease trading but this effect is reduced as the trader's track record extends. The learning about ability models interpret this as the speed of learning about the trader's skill level decreasing over time.

We can push this analysis a little further since demographic characteristics give us a cross sectional dimension to the test. A novice trader typically learns a lot about his likely level of trading skills by trading. This speed of learning is likely to be greater the less informed about his ability the trader is initially. In particular, young novice traders are likely to be less informed about their abilities than an older novice trader since the older trader may also have received signals about his skill level as a trader from his life experiences. We therefore expect younger (older) traders' quit decisions to have greater (lower) sensitivity to trading performance. Figure 1 confirms this intuition. The evolving sensitivity for older traders is always above that of younger traders, implying that performance has a lower impact on older traders' decision to quit than younger traders' decisions even though they both have the same trading experience.

3.3 The reaction to a signal

A second implication of traders learning about their abilities is that trading becomes more attractive after successes and less attractive after failures. This could manifest itself in several ways. Traders receiving a positive signal about their ability could increase their average trade size, trade more times per trading day, or trade more frequently. We test the first two responses jointly by regressing the log of the US dollar value of trades on day t on day *t-1*'s success indicator and a lagged dependent variable. Traders who exit on day t are excluded from the regression since we already know that a loss increases the likelihood of quitting. The regression therefore measures whether outcomes affect trades size even after excluding exits.

< Table 4 about here >

The estimates in Table 4 indicate that profitable trading on day t leads to a 19% increase in the volume traded on the next active day relative to a trader making a loss on day t. We can again condition the analysis on the career status of the trader. Success during the first trades ($N<=10$) sees trade volumes increase by more than 20%, but this slightly falls to 18.8% for late career trades ($N>50$). More distinctly, older traders increase their trade volumes by less than younger traders (21.4% versus 15% respectively). These findings are again supportive of a decreasing impact of a signal as traders become more experienced, either through having traded for longer and especially through being older.

Trading volumes are very volatile and we repeat the analysis with the dependent variable being an indicator variable taking the value of one if there is an increase in the volume traded on the next active day and zero otherwise. This is a simple linear probability model testing the effect of profitable trading on day t on the probability of increasing trading volumes on the next active day. Again we run this regression for the full sample and conditioned on the career status and age quintile of the traders. Results are reported in panel B of Table 4. The coefficients on the success indicator are all positive and highly significant, and suggest that volumes traded on day t are around six percent more likely to increase relatove to volumes traded on day $t-1$ if day $t-1$ was a sucessful trading day. The magnitude of the effect shows the same slightly declining trend with experience but sensitivity to the trading signal is most clearly inversely related to the age of the trader.

Traders also trade more frequently following a positive signal about their abilities. In panel C of Table 4 we replace the volume of trade with the gap in days between active trading days as dependent variable. The coefficient on the lagged success signal is, as expected, significantly negative indicating that a positive signal of ability results in a shortening of the gap between trading activity. This effect is smaller for more experienced traders ($N > 50$) than novice traders. Again, the impact of success is much larger for younger traders than for older traders.

The results of sections 3.2 and 3.3 show that traders change their behaviour in response to signals about their performance. A positive signal makes them more likely to continue trading and to trade both more frequently and in greater volume. These findings are consistent with all classes of learning models. To delve a little deeper, we consider the actions of traders when the signal they have received is not very strong. Specifically, we perform an analysis in the spirit of a regression discontinuity design and consider how traders alter their trading volume in response to profits or losses that are very close to zero.

In our analysis to date, a successful trading day has been defined by a positive profit irrespective of the size of the profit.[14] Results based on this simple indicator suggest that, compared to a non-profit day, a profitable trading day increases the probability of trading in higher volume on the next active day by almost six percent. In Figure 2 we plot the average probability of increasing trade volumes in period $t+1$ for different values of day t profit or loss, together with two fitted fourth order polynomials, one each for profits and for losses.[15] Three features of this plot are apparent. First, and consistent with the regression results, the probability of increasing subsequent trading volumes is higher following profits than losses. Second, the probability of increasing trade volume on the next trading day increases as we approach zero from either side. A gain or loss of just a few cents has the largest impact on subsequent trading volumes. Note that this effect is not driven by abnormally low trading volume on day t generating small profits or losses which is then followed by more normal volumes on day $t+1$. We obtain a very similar pattern if we only consider the efect of day t profits and losses generated by volumes that are above average for that trader. Third, there is a significant discontinuity at zero. While the probability of increasing subsequent trade volume is high for the very smallest losses (close to 50%), the probability jumps by around four percent for the very smallest profits. That is, a loss of one cent has a significantly smaller effect on the probability of increasing trade volume than a gain of one cent.[16] It is hard to reconcile the second two features of the plot with rational learning. A rational trader seeking to learn about her ability ought to make very similar inference from making a few cents as he does from losing a few cents, yet the discontinuity at zero suggests this is not the case. Similarly, in a rational learning by doing framework, the most informative events are likely to be large gains (or losses). Yet the probability of trading more in the next period peaks following

[14]Recall that we cannot reliably calculate returns due to data limitations.

[15]The plot excludes traders who quit trading immediately after t and we exclude the profit or loss from the first trading day of each trader. We also exclude observations with exactly zero profit or loss from this plot.

[16]A formal regression discontinuity design analysis using the approaches detailed in Calonico, Cattaneo, and Titiunik (2015) confirms the magnitude and high statistical significance of the switch from loss to profit.

the very smallest gains or losses.[17]

The findings are instead more supportive of some form of behavioural biases in learning. We explore this further in subsequent sections.

3.4 Persistent losers

The literature has noted a problem with similar analyses of retail investors in different asset classes. If traders learn by doing, then long-lived traders should be profitable since they have learned to be competent. Similarly, within a rational learning about ability context, novice traders will be willing to incur small losses on average on their trades as long as there is a large enough positive expected payoff to learning that they have trading skills. While there is evidence that retail investors in equity markets learn by trading, the puzzle remains that even very experienced market participants are not, on average, successful. The average equity retail trader does not learn to be profitable, either by learning how to trade or by learning that he has innate ability and should persist. Non-rational learning about ability models are more consistent with the evidence in this regard. Unduly optimistic traders trade too frequently and too aggressively, both of which reduce expected returns. In these models, investors may learn to fail.

$<$ Table 5 about here $>$

We investigate the performance of our traders in Table 5. This table reports average performance statistics for traders with differing lifespans. We report three performance statistics: the average daily profit or loss measured in dollars, the success ratio, and an indicator variable 'Winner' that takes the value unity if the trader had a positive cumulated profit at the end of his trading career.[18] The average value of this final indicator tells us the proportion of traders that finished with a profit. We consider traders with differing lifespans (N^*) given in the column heading. The first row of each panel gives lifespan averages. So, for example, traders active for between 10 and 25 days make an average daily loss of $20.66 over their trading lifetime. Subsequent rows give statistics

[17] We performed a similar analysis on the decision to quit however unreported results reveal no particularly anomolous behaviour and the probability of quitting is monotonically declining in profit, even around the breakeven point.

[18] Or when the sample ended if the trader is right censored.

for first ($N \leq 10$), early ($10 < N \leq 25$), intermediate ($25 < N \leq 50$) and late ($N > 50$) trades. So, those same traders active for between 10 and 25 days make an average daily loss of \$11.43 over their first ten trading days but this rises to an average loss of \$44.23 for the trades made between day 11 and their final trading day.

The first column of figures suggest that the most short-lived traders ($N^* \leq 10$) perform noticeably badly using all three performance statistics. They make losses of \$34.61 per trading day on average, make money on just 39% of trading days, and less than ten percent make money over their (short) trading lifespan. This is what we should expect from all models of learning. Traders that cease trading after relatively few periods have either concluded that they have no skill, or have not spent much time honing their trading techniques and so have not learned how to trade well. They would therefore be expected to perform badly.

As expected, full sample performance statistics broadly improve as the lifespan of traders increases - average losses fall, success ratios rise and larger proportions make profits over their trading careers. However, career performance statistics remain poor as experience rises. All experience categories on average lose money and the proportion of traders that win over their career remains low irrespective of experience.

These full-sample statistics are averages over the entire life of traders. Our earlier results show that traders alter their behaviour after signals of their abilities. In a learning by doing model, poor initial performance improves as traders learn how to trade. In learning about ability models, traders receiving positive signals increase their trading activities. While traders in our sample do not pay any fixed trading costs, if effort is also correlated with activity performance should also evolve, positively in a rational model but perhaps negatively in a non-rational one. The early-career performance of long-lived traders is therefore potentially different to their late-career performance.

The results in Table 5 support an evolution of performance, though not in the way the rational learning models predict. Traders that will go on to have long trading careers ($N^* > 50$) tend to have made comparatively small losses and have good success ratios in their first few trades ($N \leq 10$). A relatively large proportion (39%) make money over their first trades. However, performance deteriorates as their experience lengthens and by their late career trades ($N > 50$) they are making large losses per trade and only win on just over 50% of trades. Just 13% of these long-lived traders are making money over their late-career trades. The signals they received early in their careers appears to have encouraged them to continue trading but performance turns increasingly negative later in their career. Such a pattern is inconsistent with a learning by doing model and not easy to reconcile in a rational learning about ability framework. A deterioration in ability is, however consistent with an irrational learning model where, for whatever reason, traders interpret signals as positive and adapt their trading strategy but in doing so take larger but inappropriate trades, resulting in increasing losses. We explore this more formally in the following section.

3.5 Learning

To get a better understanding of the learning processes at play we estimate a series of regressions relating performance to experience. We begin with a simple model that we estimate at a monthly frequency:

$$y_{i,t+1} = \alpha + \beta_1 Experience_{i,t} + \beta_2 Experience_{i,t}^2 + \delta X_{i,t} + \epsilon_{i,t} \tag{2}$$

where the dependent variable is a measure of monthly performance. We use three measures of performance: a success indicator that takes the value one if positive total profits are made over the month, zero otherwise ("Win"); total cumulated profit over the month ("PL", measured in USD); and a proxy for return equal to total cumulated profits over the month divided by the volume traded during the month multiplied by 100 ("Ret"). We use monthly performance measures in this section for two reasons. First, the Ret measure is extremely volatile when measured at higher frequencies since it apportions marked-to-market profits to days with low or no trading activity. Aggregating over a month, while still imperfect, better balances trading profits and traded volumes. Second, later in this section we use a Heckman correction for selection bias that entails estimating a separate selection equation for each period in the sample. Working at a daily frequency this would mean estimating almost 600 selection regressions and including almost 600 additional terms in the second-stage regression. While arguably this is possible due to the large size of our dataset, the use of daily selection equations would imply we capture an individual's decision to trade on day t. This is likely driven by many factors outside our dataset such work commitments, vacations, or illness. Experimentation suggests that daily selection equations work very poorly. Conversely, moving to a monthly frequency reduces the number of selection equations needed and improves our ability to capture factors driving the decision to trade in any given month.

The key explanatory variable *Experience* is a proxy for investors' trading experience. We proxy for trader experience by either the number of days on which the trader has been active ("$LifeSpan$") or by the log of the cumulative number of trades made ("$TradeCount$"). Both variables are calculated using the history of the traders until the start of the month in which performance is calculated. We allow traders to learn faster during their earlier years by including $Experience^2$. We also include a set of control variables, $X_{i,t}$, namely lagged log trade volume and lagged log number of deals, plus month-year time effect dummies.

A positive coefficient on *Experience* in this regression would reflect learning by doing effects if attrition is exogenous and traders are not heterogeneous. Since both of these assumptions are strong and, given our earlier results, unlikely to hold for our data we relax them in subsequent specifications.

< Table 6 about here >

The results of estimating Equation 2 are reported in the first two columns of Table 6.[19] Win-$LifeSpan$ and Ret-$TradeCount$ combinations suggest rational learning, but other combinations are insignificant. However, these OLS results are merely reported to help benchmark our later ones since our previous results suggest that traders are heterogeneous and that attrition is endogenous. Equation 2 is then misspecified and learning effects are potentially incorrectly estimated. We first deal with the heterogeneity issue.

Since trader participation in our sample changes over time, trader heterogeneity may induce cohort effects. For example, if innate heterogeneous ability positively correlates with the number of trades places by an investor, Equation 2 would confuse fixed-ability where better traders trade more with learning. We can account for unobserved trader

[19] The results reported use OLS but we obtain similar findings if we use logit methods when the Win measure, a binary indicator variable, is the dependent variable.

heterogeneity by exploiting the relatively long time-series dimension of our data and include fixed effects in the regression:

$$y_{i,t+1} = \alpha_i + \beta_1 Experience_{i,t} + \beta_2 Experience^2_{i,t} + \delta X_{i,t} + \epsilon_{i,t} \tag{3}$$

Accounting for heterogeneity has a substantial impact on our results, as documented in columns 3-4 of Table 6. Most obviously, any evidence of rational learning has disappeared and the performance of traders worsens as their experience grows. The magnitudes of the estimated "learning-to-fail" effects are quite large. A trader with a $LifeSpan$ of 100 days is 12% less likely to have a winning month than a complete novice trader. Alternatively, the *Ret* of a trader with 100 days' experience is 4.6bp lower than that of a novice.

Since we know the decision to quit is related to performance, our fixed effects estimates still potentially suffer from endogenous attrition. To assess whether this is a serious issue for our estimates we use a variant of the Verbeek and Nijman (1992) variable addition test. This entails including a lagged selection term $s_{i,t-1}$ into the fixed effects model, where $s_{i,t} = 1$ if trader i trades after period t and is zero otherwise. The Verbeek-Nijman test statistic is extremely significant in all specifications of the model, implying that selection is important in the sample and that attrition is not exogenous.

We account for both endogenous attrition and cross-sectional heterogeneity using a variant of the Heckman selection model due to Wooldridge (1995). This approach entails estimating a first stage Heckman selection model that predicts which observations will be observable in the second stage learning model for each monthly cross-section. The conditional probability that an individual continues to trade (the inverse Mills' ratio) of each selection equation is then included in the learning regression model which corrects for the selection issue. The second stage learning model is estimated in first differences to account for individual time-invariant heterogeneity. Specifically, the second stage regression we estimate is:

$$\Delta y_{i,t+1} = \beta_1 \Delta Experience_{i,t} + \beta_2 \Delta Experience^2_{i,t} + \delta \Delta X_{i,t} + \rho_1 I(t=1)\lambda_1 + ... + \rho_j I(t=j)\lambda_j + \epsilon_{i,t} \tag{4}$$

where $\lambda_1, ..., \lambda_j$ are the inverse Mills' ratios from the selection models in month 1 to j, and $I(t = j)$ is an indicator variable equal to unity in month j and zero otherwise.

The first stage selection model use a set of cross-sectional probit regressions to predict whether or not a trader trades in a given month. It is desirable to have at least one instrument in the selection equation to ensure identification.[20] The probit regressions include a constant, both performance measures (Win_{t-1} and Ret_{t-1}), linear and quadratic experience terms (with experience proxied by either $LifeSpan$ or $TradeCount$), and an instrument similar to that use by Seru, Shumway, and Stoffman (2010) that takes advantage of the demographic characteristics we have available. The instrument is the proportion of all traders from the trader in question's city that choose to trade in that month (*PropActive*), and the argument is that an individual is more likely to trade if his neighbours are trading. This is motivated by the work of Hong, Kubik, and Stein (2004) and Ivkovic and Weisbenner (2007) who claim that there is a social component unrelated to performance that drives at least part of investor trading (while acknowledging that there may be other common factors driving trader activity). Identification relies on this social component.

The variables included in the first stage selection equations, including the instrument term, are each significant in most of the cross sections suggesting that they work well in explaining the traders' decisions to trade each month. For brevity, we only report pooled first-stage estimates in Table 7, using either $LifeSpan$ or $TradeCount$ the experience proxy. Results for each of the months are qualitatively similar to those reported. As expected, there is strong evidence that as investors perform poorly they cease trading. In particular the estimates on Win_{t-1} and Ret_{t-1} are both positive and very strongly significant. Consistent with earlier findings, this shows that as low ability traders learn about their inherent ability by trading and eventually cease. More successful traders continue to be active. The other coefficient estimates reported in Table 7 are also sensible: traders are more likely to trade if they have more trading experience though at a decreasing rate, and, importantly, the coefficient estimate for our instrument is statistically significant and of the predicted sign. Specifically, a higher proportion of traders in the same city that are active in a given month increases the probability that the individual will trade in that month.

[20] The non-linearity of the inverse Mills' ratio may be sufficient to allow identification. However, the exclusion restriction that follows from including a variable in the first stage regressions but not in the second stage model aids identification.

The key coefficient estimates from Equation 4 are given in the final columns of Table 6. We note first that the joint test of $\rho_j = 0$ for all months is strongly rejected in the second stage regression, indicating the presence of important selection bias effects consistent with the Verbeek-Nijman results (unreported p-values are all < 0.001). Second, and irrespective of the permutation of performance and experience proxies, all experience coefficients are significantly negative. As with the fixed effects estimation, traders appear to perform worse with experience. The quadratic terms are all positive, but are only statistically significant in Panel A where the experience proxy is given by $LifeSpan$.

While the signs of the coefficients are similar to those obtained using fixed effects, coefficient magnitudes are smaller once selection issues are taken into account. Based on the Heckman regression estimates, a trader with a $LifeSpan$ of 100 days is 5.8% less likely to have a winning month than a complete novice trader. Alternatively, the Ret of a trader with 100 days' experience is 3.1bp lower than that of a novice. Proxying experience with $LifeSpan$ suggests that performance deteriorates until a trader has been active on around 380 days. By this time his Ret performance is 6.6bp worse than a novice (and his probability of a winning month is 9.4% worse). Very few of our traders are so experienced, however, with fewer than 1% having 380 days of trading experience. Quadratic terms are insignificant when we proxy experience with $TradeCount$. Nevertheless, even using the point estimates reported in Table 6 performance deteriorates continually as we move well into the extreme tail of experience. After 5,000 trades - well into the 99th percentile of the $TradeCount$ distribution - a trader's monthly Ret is 1.2bp less than that of a novice trader and his Win probability is 3.2% lower.

The evidence in this section helps differentiate between competing learning hypotheses. Once we account for heterogeneity and selection effects, there is strong evidence of irrational learning by traders. Retail FX traders with more experience tend to underperform those with less experience. There is weak evidence that performance eventually improves but very few traders in our sample are sufficiently experienced to reap any benefits (and hence our estimates of long-term learning effects are very imprecise). Nevertheless, the magnitude of the irrational learning effects are relatively small. The learning about ability effects we have documented earlier are much more important. Traders mainly learn by realising that they have no skill and hence ceasing trading.

4 Conclusion

We analyse the performance of almost 100,000 retail foreign exchange traders over two and a half years. Our focus is on whether and how traders learn in this previously under-explored marketplace. In particular, we attempt to distinguish between the three main categories of learning seen in the literature:

1. Learning by doing, whereby traders get better at trading through experience
2. Rational learning about ability, where traders who are initially uncertain about their innate trading skills rationally update their estimates of their ability based on their performance
3. Irrational learning, where traders also update their estimates of their own skill levels based on trade performance or revise their trading techniques based on experience in irrational ways, perhaps due to behavioural tendencies such as overconfidence or attribution bias.

We find four main pieces of evidence. First, traders are significantly more likely to cease trading after a day on which they lose money (i.e. after they receive a negative signal about their ability). The sensitivity of this decision to quit following a negative signal is much larger for traders that are likely to be learning the most. Novice traders and young traders react most to performance signals, while more experienced traders and older traders, who might have already learned either through being in the market for longer or through their life experiences, react much less.

Second, traders trade both more frequently and in greater volume following a positive signal. Traders may be willing to make expected losses on their initial trades while they either learn how to trade effectively or what their innate skill levels are. To minimise costs, however, they should choose to trade only relatively small amounts. As they learn how to trade or as they receive positive signals about their abilities trading becomes more attractive and so they trade more and in larger amounts.

While broadly consistent with both rational learning by doing and learning about ability models, there are some aspects that appear non-rational. Foremost among these is the tendency for very small (sub-dollar) gains and losses to be followed by increased trading activity with much higher probability than more substantial gains. It is difficult to understand why a profit of a handful of cents leads to a more substantial revision of trading activity levels than a profit measured in hundreds of dollars. Further, gains of a handful of cents are also more likely to result in increased trading activity than are losses of a handful of cents despite there being no material difference between these two outcomes given the volumes being traded. These two findings suggest that there are non-rational learning elements at play.

Despite the encouraging results for learning models we also show that traders - even very experienced traders - perform poorly. This is common to the literature on retail traders' performance. Most retail FX traders make losses from trading on average, and these losses are not confined to their early trades. This is harder to reconcile with learning by doing or with rational learning about ability models. It is more consistent with irrational learning approaches where traders interpret signals about their abilities in overly positive ways, adapting their strategies but in doing so taking on inappropriate trades and making increasing losses.

Our final set of results explicitly test for the relationship between performance and experience. Our empirical approach takes into account two key characteristics observed in the data. First, some traders are clearly better than others and, second, attrition is endogenous and the decision to quit is related to performance. Having corrected for these important effects we demonstrate that the balance of evidence points to a relatively small but statistically significant deterioration in performance with experience. We interpret this as traders learning to fail due to irrational learning.

Overall then, we find evidence supporting the hypothesis that traders learn about their abilities by trading, though this does not appear to be fully rational. We also find evidence of irrational learning with experience. The concerns of regulators regarding this market may be justified. While some retail traders learn that they should not be active in this market and quit following losses, others irrationally continue to trade and simply make more losses. In common with other retail investment markets, only a small proportion of retail foreign exchange traders make profits.

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Table 1: Descriptive Statistics

	Mean	25 percentile	Median	75 percentile	Std. Dev.
Active days	45	8	20	51	68
Avg daily trading volume ($)	n.d.	14,651	41,047	115,291	1,307,496
Avg daily number of trades	n.d.	4	7	12	9.6
Avg daily profit ($)	n.d.	-19.36	-5.56	-1.48	141
Avg success rate	0.48	0.37	0.50	0.61	0.21

Notes: n.d. denotes not disclosed for confidentiality reasons.

Table 2: Trade Performance Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	Full	Full	Full	$N \leq 10$	$10 < N \leq 25$	$25 < N \leq 50$	$N > 50$	Age Q1	Age Q5
Career success rate	0.415	0.411	0.417	0.157	0.474	0.674	0.895	0.306	0.537
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)	(0.006)	(0.005)	0.008
Year/month dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Experience dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.022	0.024	0.024	0.011	0.029	0.039	0.044	0.016	0.034
Std Dev. of Career success rate	0.179	0.179	0.179	0.307	0.173	0.143	0.117	0.198	0.167

Notes: This table reports the results of regressing a success dummy of trading day t (1 if profit, 0 if loss) on the career success ratio up to but not including time t plus dummy variables, as noted. Standard errors are reported in parentheses under coefficient estimates. Columns (4)-(7) restrict the sample according to trader experience. Column (8) examines traders in the youngest age quintile and column (9) examines the oldest quintile of traders. All standard errors are clustered by trader and are robust to heteroscedasticity.

Table 3: The Decision to Quit

	(1)	(2)	(3)
Success (t-1)	0.842	0.840	0.836
	(0.008)	(0.008)	(0.008)
Career success rate (t-1)	0.848	0.855	0.875
	(0.017)	(0.0178)	(0.018)
Year/month dummies	No	Yes	No
Controls	No	No	Yes

Notes: This table reports the results of estimating a Cox proportional hazards model with a success dummy of trading day t-1 (1 if profit, 0 if loss) and career success ratio up to time t-1 plus dummy and control variables, as noted. The control variables are logged career-to-date t-1 cumulated trading volumes and number of trades. Standard errors are reported in parentheses under coefficient estimates.

Table 4: The Effect of Success on Trade Activity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	Full	$N \leq 10$	$10 < N \leq 25$	$25 < N \leq 50$	$N > 50$	Age Q1	Age Q5
Panel A: Trade volume							
Success (t-1)	0.177	0.183	0.177	0.179	0.172	0.194	0.140
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Volume (t-1)	0.753	0.653	0.736	0.763	0.788	0.716	0.763
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Panel B: Trade volume increase indicator							
Success (t-1)	0.0576	0.0623	0.0597	0.0592	0.0537	0.0618	0.0454
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Panel C: Trade Intensity							
Success (t-1)	-3.470	-4.662	-4.914	-4.258	-2.203	-4.687	-2.356
	(0.026)	(0.067)	(0.060)	(0.0527)	(0.027)	(0.063)	(0.046)
Intensity (t-1)	0.024	0.022	0.022	0.025	0.029	0.017	0.039
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.017)	(0.003)

Notes: Panel A of this table reports the results of regressing the log of the volume of trades on day t on a success dummy of trading day *t-1* (1 if profit, 0 if loss), a lagged dependent variable, and year-month and experience dummy variables. Standard errors are reported in parentheses under coefficient estimates. Columns (3)-(6) restrict the sample according to trader experience. Column (7) examines traders in the youngest age quintile and column (8) examines the oldest quintile of traders. In Panel B the dependent variable is an indicator variable that takes the value of one if the volume of trades on day t is greater than the volume traded on trading day $t-1$. No lagged dependent variable is included in this case. Panel C repeats this exercise with the difference between active days (measured in days) as dependent variable and with a lagged dependent variable included in the regression. All standard errors are clustered by trader and are robust to heteroscedasticity.

Table 5: Performance and Experience

Lifespan:	$N^* \leq 10$	$10 < N^* \leq 25$	$25 < N^* \leq 50$	$N^* > 50$
Panel A: Average profit				
Full	-34.61	-20.66	-17.11	-18.60
$N \leq 10$	-34.61	-11.43	-4.73	-5.18
$10 < N \leq 25$		-44.23	-15.24	-13.45
$25 < N \leq 50$			-41.12	-15.57
$N > 50$				-33.63
Panel B: Success ratio				
Full	38.65	51.14	53.65	55.43
$N \leq 10$	38.65	55.13	56.03	54.61
$10 < N \leq 25$		39.46	55.53	54.99
$25 < N \leq 50$			43.54	55.38
$N > 50$				51.95
Panel B: Winners				
Full	9.77	14.28	16.08	15.79
$N \leq 10$	9.77	35.50	39.98	38.65
$10 < N \leq 25$		9.69	32.70	34.06
$25 < N \leq 50$			10.51	29.50
$N > 50$				13.39

Notes: The table reports the cross-sectional mean average daily profit measured in dollars, the mean success ratio (100.profitable days/total number of active days), and the proportion of traders that are profitable("Winners"), broken down by trader lifespan in columns (denoted N^*) and experience in rows (denoted N). The first row in each panel gives the performance measure over the full lifespan of the trader. Subsequent rows give the performance measure over the traders' first ($N \leq 10$), early ($10 < N \leq 25$), intermediate ($25 < N \leq 50$) and late ($N > 50$) trades.

Table 6: Learning Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	FE	FE	Heck	Heck
	Win	Ret	Win	Ret	Win	Ret
Panel A:						
$LifeSpan_t$	0.459	-0.008	-1.415	-0.535	-0.667	-0.362
	(0.045)	(0.010)	(0.069)	(0.017)	(0.076)	(0.020)
$LifeSpan_t^2$	-0.922	0.073	2.131	0.762	0.855	0.502
	(0.147)	(0.028)	(0.151)	(0.035)	(0.161)	(0.040)
Panel B:						
$TradeCount_t$	0.029	0.033	-0.240	-0.077	-0.070	-0.026
	(0.025)	(0.004)	(0.038)	(0.010)	(0.030)	(0.008)
$TradeCount_t^2$	0.006	-0.011	0.079	0.025	0.015	0.007
	(0.024)	(0.003)	(0.067)	(0.008)	(0.018)	(0.006)

Notes: Panel A of this table reports the results of estimating equations 2 - 4. The dependent variable in each regression is a measure of monthly performance captured by one of two proxies: a success indicator that takes the value one if positive total profits are made over the month, zero otherwise (Win) and a proxy for return equal to total cumulated profits over the month divided by the volume traded during the month multiplied by 100 (*Ret*). The proxy used as dependent variable is given in the third row of the table. The key explanatory variables are *Experience* and *Experience*^{2}. In Panel A the proxy for *Experience* is the number of days on which the trader has been active/1000 ($LifeSpan$) while in panel B the proxy is the cumulative number of trades made/10,000 ($TradeCount$). The second row of the table gives the estimation method used (OLS, fixed effects or a Heckman-style model as detailed in the text). Standard errors are given in parentheses below coefficient values. All standard errors are clustered by trader and are robust to heteroscedasticity. All regressions also include month-year dummies, lagged monthly trading volume and lagged monthly number of trades. The Heckman-style model also includes separate inverse Mills ratios estimates for each month in the sample.

Table 7: First Stage Heckman Selection Regressions

	$LifeSpan$	$TradeCount$
Win_{t-1}	0.774	0.785
	(0.006)	(0.006)
Ret_{t-1}	2.104	1.828
	(0.025)	(0.025)
$LifeSpan_t$	9.654	
	(0.972)	
$LifeSpan_t^2$	-15.811	
	(0.352)	
$TradeCount_t$		3.435
		(0.040)
$TradeCount_t^2$		-1.012
		(0.023)
$PropActive_t$	1.335	1.193
	(0.067)	(0.066)
Pseudo-R^2	0.135	0.110

Notes: This table reports results of pooled selection regressions. The dependent variable is an indicator variable that takes the value one if the trader was active during month t, and zero otherwise. Traders enter the sample in their first active month. The explanatory variables are lagged performance (Win_{t-1} and Ret_{t-1}), experience to the start of month t proxied by either $LifeSpan$ or $TradeCount$, quadratic experience terms, and the proportion of traders in the trader in question's city that trade in month t ($PropActive_t$). Regressions also include month-year dummies.

Figure 1: The Effect of Success on Propensity to Quit

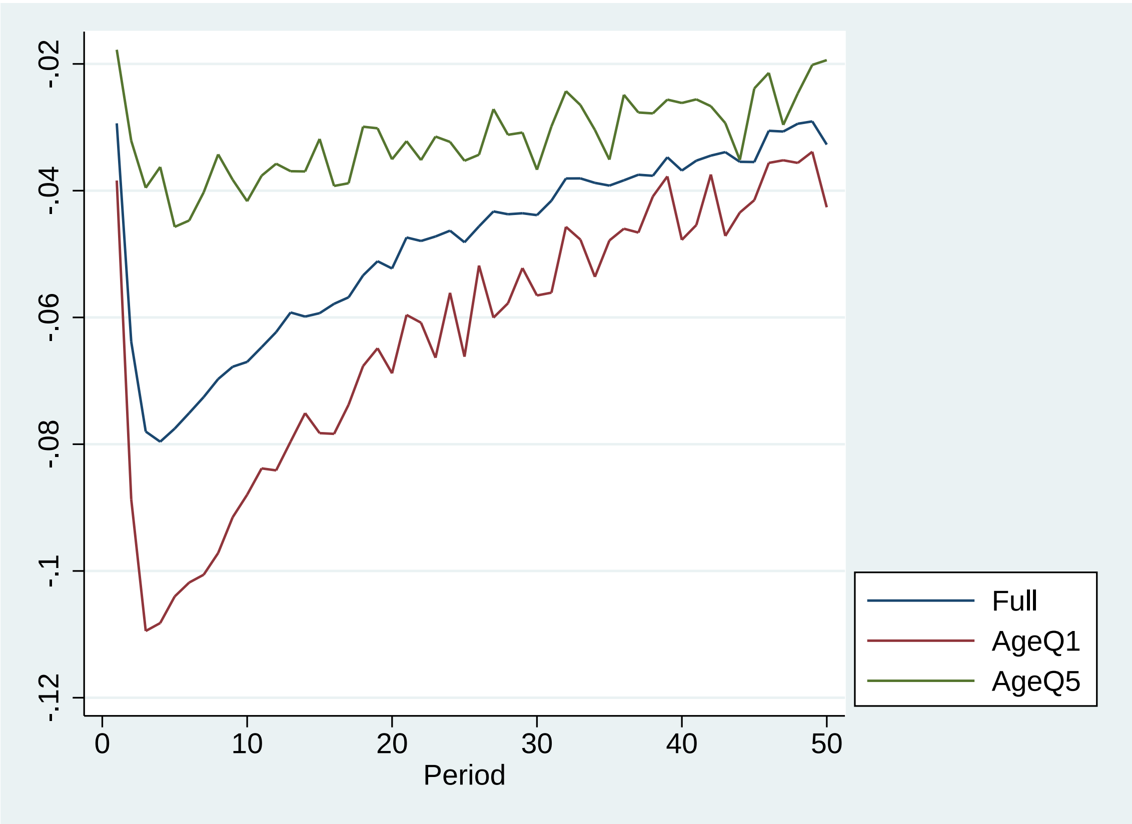

Figure 2: The Effect of Profit and Loss on the Probability of Increased Volume