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ScienceDirect
Journal of Financial Markets 12 (2009) 317–336
Journal of FINANCIAL MARKETS
www.elsevier.com/locate/finmar

Do individual investors learn from their trading experience?☆

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Available online 29 July 2008

Abstract

After analyzing retail investors' stock trades for potential learning behavior, we present evidence that individual investors learn from their trading experience. Initially, we question whether investors' previous forecasting ability (inferred from prior purchases' subsequent risk-adjusted performance) affects their future trade profitability and activity. Indeed, as an investor's inferred ability increases, so does her ensuing trade profitability and intensity. Further, because additional investment experience allows more accurate ability inference, we posit that trading experience should help investors obtain better investment performance. Consistent with this hypothesis, not only do excess portfolio returns improve with account tenure, but we also find that trade quality (i.e., average raw and excess buy-minus-sell returns) significantly increases with experience (i.e., calendar time and account tenure). In sum, individual stock investors do learn, and they consequently adjust their behavior and thus effectively improve their investment performance.
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JEL classification: D19; G14

Keywords: Learning; Individual investors; Rationality; Trading

☆We thank Brad Barber, Jim Clayton, Michael Ferguson, Brain Hatch, Yong Kim, Brian Kluger, Avanidhar (Subra) Subramanyam, Steve Slezak, Steve Wyatt, Juhani Linnainmaa, anonymous referee, and seminar participants at University of Cincinnati, Beijing University, UC Davis, Financial Management Association meeting (New Orleans) for constructive comments. Zhu acknowledges National Natural Science Foundation of China (Grant no. 70432002) All errors are ours alone.
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doi:10.1016/j.finmar.2008.07.001

1. Introduction

Given the mounting evidence that investors make various mistakes, much attention has recently been paid to agent rationality (see, e.g. List, 2003; Dhar and Zhu, 2006, among others), a classic assumption in modern economics and finance that simplifies decision-making with analytical models. However, judgment errors alone do not violate rationality. That is, the assumption of rational expectations "does not deny that people often make forecasting errors, but it does suggest that errors will not persistently occur on one side or the other" (Sargent, 1993). In other words, agents are not likely to make *systematic* mistakes. Determining whether investors learn from their experience—specifically, whether trading experience affects behavior and, perhaps more importantly, improves investment performance—would be a significant step towards establishing the appropriateness of the rationality assumption.

The learning process that exists within a real market setting with potentially semi-rational or limited rational investors is not well-understood. Empirical psychology literature is often used to justify the assumptions employed in most existing theory, such as Daniel, Hirshleifer, and Subrahmanyam (1998) and Gervais and Odean (2001) who contend that investors may learn about their private signals' precision through a mechanism more complex than the neo-classical economic assumption of Bayesian updating. However, despite the many advantages of laboratory experiments, the results regarding individual learning seem to be mixed.[3] Further, not only does the laboratory setup fail to accurately capture investor behavior when significant wealth is at stake, but the subjects also deal with relatively simple signals and tasks, leading to more restricted learning. In contrast, learning in a trading environment can be more challenging. Although trade outcome (i.e., profitability) can be easily judged, individuals inferring their forecasting ability (a proxy for their private signal precision) must sift through much more noise such as benchmark performance and risk undertaking. Finally, while data limitations have hindered past empirical endeavors, detailed personal portfolio information combined with market condition data enable us to track discount investors' trading activity and ability discovery from account inception, providing a direct test of investor learning. Thus, in addition to improving the understanding of individual learning behavior, our examination into trading environment learning processes will help differentiate learning in a complex setting from that in an experimental setting.

We analyze possible individual investor learning behavior from two perspectives, the first being based on the relation between trade performance and trading behavior. Following Daniel, Hirshleifer, and Subrahmanyam (1998) and Gervais and Odean (2001), we argue that investors' demand for risky assets will increase with their confidence in their private signal precision. Specifically, if investors privately receive signals (e.g., ranging from negative one to positive one) regarding the quality of potential purchases' future returns, then investors who believe their signals to be perfectly accurate (based on their previous trades' subsequent returns) would be willing to trade whenever the signals were, even marginally, positive. However, if investors believe their signals to be less accurate, then they would be less willing to trade after receiving only slightly positive signals. Clearly, investors' willingness to trade would increase with their perceived signal precision.

[3]Coursey, Hovis, and Schulze (1987), Dhar and Zhu (2006), Erev and Roth (1998), List (2003), and Shor (2004) find that experience helps investors reduce certain behavioral biases and that subject behavior improves over time. In contrast, Knetsch and Sinden (1984) and Camerer and Hogarth (1999) argue that learning can take a long period of time and may not be effective in eliminating behavioral biases.

We then test the natural consequence, i.e., whether the perceived precision of prior private signals significantly affects individual investors' future trade performance and activity. To approximate investors' private signal precision, we use a nonparametric statistical model developed by Henriksson and Merton (1981), modified by Cumby and Modest (1987), and applied by Hartzmark (1991) and others. Working backwards, if transaction profitability and hence apparent trading ability is dependent on signal accuracy, then analysis of the subsequent performance of signal-conditioned previous trades should partially reveal the prior noisy private signals' precision. This framework enables us to construct two trading ability time-series measures—''consistent forecasting ability'' and ''big hit forecasting ability''—which respectively proxy for (i) the precision of information regarding the *signs* of future excess stock returns, and (ii) the precision of information regarding both the *magnitudes* and *signs* of future excess stock returns. Our empirical results provide strong evidence that these ability measures significantly affect investors' future investment performance and trade intensity. Fixed effect panel regressions indeed suggest that if previous private signals are believed to be more (less) accurate, then investors' future purchases are more (less) likely to generate positive risk-adjusted excess returns and their future trading activity increases (decreases).

The second perspective from which we analyze investors' possible learning behavior is based on the relationship between trading experience and investment performance. Recent studies have shown that experience can play a significant role in eliminating judgment errors, such as the endowment effect (List, 2003) and the disposition effect (Dhar and Zhu, 2006). Likewise, we expect that trading experience will help individuals learn about their private signal precision, which will consequently improve their performance by enabling them to make better signal-driven trades—presumably by trading more (less) aggressively when faced with more (less) precise private signals.

As anticipated, we find strong evidence that trading experience (measured in a variety of ways related to inferred private signal accuracy) helps future investment performance. First, as an individual's investment experience (number of elapsed months since account opening) increases, so does her portfolio's future risk-adjusted return. This effect is particularly strong for inactive traders and traders with average or below-average investment performance. Second, to capture dynamic portfolio changes, we also perform calendar-time portfolio analyses on trades made by investors at different stages of their investment tenure. We find very robust results that the portfolios mimicking more-experienced investors' trade decisions outperform the portfolios mimicking less-experienced investors' trade decisions by up to three basis points per day, controlling for common risk factors. In sum, our evidence suggests that trading experience helps improve individual investor welfare.

The rest of the paper proceeds as follows. Section 2 describes the data; Section 3 analyzes the relation between prior trading ability and future trade performance and intensity; Section 4 analyzes the effects of trading experience on portfolio performance; and Section 5 concludes.

2. Data

Our analyses are based on a sizeable panel data set containing the trading activities of individuals at a large national discount brokerage firm (see Barber and Odean (2000) for further data descriptions). The data, which cover the investments of 77,995 households from January 1991 to December 1996, have three important components: (1) a position file that includes the end-of-month portfolio holdings for all households; (2) a trade file that records all trades executed by sample investors; and (3) an investor characteristics file that includes investor characteristics such as investors' income levels, occupation categories, ages, and the dates on which they opened their accounts. While both the trade and position files include common stocks, mutual funds, and other securities (e.g., American Deposit Receipts, fixed income securities, and options), we only focus on the common stock portions. Previous studies provide greater detail about the data and, after comparing sample investors with the Survey of Consumer Finance, ascertain that it is a good representation of national individual investors (Barber and Odean, 2000; Dhar, Goetzmann, Sheperd, and Zhu, 2004).

This data set has several features that dramatically facilitate our research. First, the data allow us to observe individuals' detailed trade histories. The inclusion of transaction prices, dates, and traded security features enables the inference of investors' security analysis abilities. Further, since the data allow us to follow individuals over a period of 6 years beginning from the time they opened their first account in 1990 or 1991, we are able to track investors' learning progression (which is naturally a temporal process).[4] Finally, the large number of individual investors contained in the data set mitigates possible sample selection problems and leads to higher inference power through the variation across individuals.

The data set is filtered as follows: First, since we focus on investors' learning about the precision of their private signals regarding stock investments, we exclude 11,535 households who do not hold common stock during any sample month. Common stocks make up roughly 60 percent of the account values and slightly more than 60 percent of all trades. Second, because the average sample household holds two accounts with the discount brokerage firm (most commonly due to retirement accounts' tax-preferred status), we aggregate monthly trades across all accounts associated with a particular household (i.e., treating multiple household accounts as one large account). Third, we only examine households whose entire trade histories are observable (i.e., those who opened their first account in 1990 or 1991), reducing our sample to 18,374 households.[5] Finally, to be in the sample at time t, household i must have non-missing data for all variables utilized in this analysis. These requirements result in a final sample of 65,118 household-months for 2,973 households, spanning the calendar time from March 1991 to November 1996. The investors included in our final sample (i) closely resemble excluded investors with respect to annual income, age, job function and amount invested in common stocks, and (ii) trade slightly more (mean number of trades = 49) than excluded investors (mean number of trades = 41).

Table 1 provides summary statistics for the trading activity definitions used in the paper (i.e., trade frequency and portfolio turnover) and reveals a wide range of trading behaviors. For example, looking at trade frequency in Panel A, the average number of monthly trades varies dramatically from a minimum of zero to a maximum of 113.0; the average number of monthly buys varies from zero to 49.67; and the average number of monthly sells varies from zero to 63.33. Similar to trade frequency, there is considerable

[4]We implicitly assume that sample investors hold no other accounts at outside discount brokerage firms. This is consistent with the Survey of Consumer Finance, which shows that, on average, households use one brokerage firm.

[5]Investors who opened their accounts after 1991 are included for a robustness check, and the results are similar.

Table 1
Data summary

This table reports summary statistics of trading frequency, turnover, and inferred trading abilities (which proxy for private signal precision) for households who opened their first accounts in 1990 or 1991 at a large discount brokerage firm. Trade frequency measures equal the total number of trades (purchases and sales), purchases only, or sales only divided by the number of months. Monthly purchase (sale) turnover is calculated as the dollar value of purchase (sale) trades executed in a month divided by the end-of (start-of)-the-month's portfolio value. Average portfolio turnover is the average of the month's purchase and sale turnover. Consistent and big hit abilities ($FS_{i,t}$ and $FB_{i,t}$) capture investors' ability to predict the direction and both the direction and magnitude of future excess returns, respectively. The two measures are defined in Eqs. (1) and (3) in Section 3.

	Mean	Median	Std. Dev.	Min	Max
Panel A: Trade frequency					
Trades/month	0.79	0.16	0.37	0.00	113.00
Purchases/month	0.45	0.08	0.20	0.00	49.67
Sales/month	0.36	0.06	0.15	0.00	63.33
Panel B: Turnover					
Avg. port turnover	0.071	0.049	0.064	0.001	0.456
Purchase turnover	0.072	0.048	0.069	0.001	0.689
Sale turnover	0.069	0.048	0.068	0.000	0.483
Panel C: Abilities					
Consistent abilities	−0.093	−0.266	0.628	−0.999	0.999
Big hit abilities	0.001	0.009	0.595	−0.999	0.999

variation in portfolio turnover (Panel B). Monthly purchase (sale) turnover is calculated as the dollar value of the purchases (sales) executed in a month divided by the end- (start-) of-month portfolio value. The average purchase and sale turnovers—7.19 and 6.90 percent, respectively—are in line with the 6.06 percent reported in Barber and Odean (2000). Total portfolio turnover is the average of the month's purchase and sale turnover. Table 1 also includes summary statistics for the trading ability measures that proxy for private signal precision, which will be discussed next.

3. Interaction between performance and trading

3.1. Inferred trading ability as proxies for private signal precision

Our learning analysis first focuses on the interaction between trade activity and performance. As mentioned, we assume that investors purchase stocks after receiving private signals, and that the purchases triggered by more precise signals will suggest superior trading ability because they will subsequently generate higher risk-adjusted abnormal returns. Further, if private signal precision is persistent, then prior private signal precision should be positively related to future private signal quality, and so ultimately should predict future transaction performance. Given this predictability, learning investors would benefit from conditioning their future trading behavior on their current inferred signal precision. For example, if an investor perceives her private signal to be imprecise (i.e., does not provide information relevant to investment performance), surmising that a signal-based stock purchase would subsequently generate a low risk-adjusted return, the investor should consequently refrain from future trading. Accordingly, we test whether previously-demonstrated trading ability (proxying for the precision of prior private signals) helps forecast first future trade performance and then future trading activity. Affirmative answers to both hypotheses would indicate that private signal precision is persistent and that investors are appropriately adjusting their trading behavior.

To test these hypotheses, we must construct measures of investors' trade activity and inferred private signal precision. Although trade frequency and turnover are straightforward choices for trade intensity measures, the selection of a trading ability proxy for perceived private signal precision is a non-trivial process. Fortunately, this is a well-studied problem in finance (see, e.g., Becker, Myers, and Schill, 1999; Henriksson and Merton, 1981; Cumby and Modest, 1987; Hartzmark, 1991; Jagannathan and Korajczyk, 1986; Merton, 1981, among many others), enabling us to adopt two widely-used measures of past trade performance to proxy for investors' inferred private signal precision.

First, we construct a proxy for the accuracy of investors' private signals regarding the *directions* or *signs* of future risk-adjusted excess stock returns. According to Henriksson and Merton (1981) and Cumby and Modest (1987), individuals have "consistent forecasting ability" (Hartzmark, 1991) if the conditional probability of correctly predicting future price changes is significantly greater than 0.5. By assuming that investors are equally capable of forecasting future price increases and decreases, we dramatically simplify the ability inference. To compute each investor's consistent forecasting ability time-series, we first estimate every stock purchase's subsequent 1-month risk-adjusted excess return.[6] A purchase's subsequent daily excess return is the stock's daily net realized return (over the Treasury-bill rate) minus the sum of the day's Fama-French factors multiplied by their respective loadings, which are first estimated by regressing the stock's daily net raw returns on the factors over the 100 trading days preceding the purchase date.[7] The purchase's subsequent 1-month excess return is calculated as the sum of these daily excess returns over the 20 trading days following the purchase date. A stock purchase is labeled "good" if it produces a non-negative subsequent 1-month excess return.

Next, we presume that investors attempting to determine their private signal precision perform the following monthly two-sided Student t-test. That is, they test whether the portion of their previous purchases which turned out to be good significantly differs from 0.5. Restated, under the assumption that the signs of excess returns are generated from a binomial process, the null hypothesis predicts that roughly half of an investor's prior purchases will be good. Using the probability significance level from this monthly hypothesis test, we follow Hartzmark (1991) and define individual i's consistent forecasting ability as of month t as

$$FS_{i,t} = (1 - probability\ significance\ level_{i,t}) \times \left(sign\ of\ \left(\frac{G_{i,t}}{N_{i,t}} - 0.5 \right) \right), \tag{1}$$

where $N_{i,t}$ is the number of purchases that the investor has made up to 20 trading days before the beginning of month t, and $G_{i,t}$ is the number of these purchases which were

[6] We focus on stock purchases instead of sales because purchase decisions seem less likely to be influenced by exogenous liquidity or tax concerns than sale decisions. Further, a variety of factors—availability and salience heuristics, individuals' exhibited sensitivity to recent performance (Barber, Odean, and Zhu, 2007b), and our sample's trade frequency (eight trades per year) and receipt of monthly account statements—lead us to select a short (i.e., 1 month) time horizon.

[7] We also estimate risk-adjusted returns using a 100 trading day window centered on the purchase date and obtain similar results.

good. The range ($-1 \leqslant FS_{i,t} \leqslant 1$) encompasses the universe of investors: those with statistically significant inferior ability (when $FS_{i,t}$ is close to -1), those with weak ability (when $FS_{i,t}$ is close to 0), and those with statistically significant superior ability (when $FS_{i,t}$ is close to 1).

The interpretation of this first proxy for information precision, consistent forecasting ability, can be illustrated with the following numeric example. Suppose that in a given month, an investor's $G_{i,t}/N_{i,t}$ equals 0.8 (i.e., 80 percent of the household's previous trades have been good, implying that this investor's previous purchases have generated more positive than negative subsequent excess returns) and its associated probability significance level is 0.15 (estimated from a t-test that the proportion $G_{i,t}/N_{i,t} = 0.5$), meaning that the null hypothesis of random subsequent excess return signs can be rejected with 85 percent confidence. In this case, $FS_{i,t} = (1 - 0.15) \times 1 = 0.85$, implying fairly precise private signals regarding the signs of subsequent purchase returns. Overall, positive (negative) measures generally suggest superior (inferior) ability or signal precision.

Next, we construct a proxy for the accuracy of investors' private signals regarding not only the *direction* but also the *magnitude* of future risk-adjusted excess stock returns. Individuals with ''big hit forecasting ability'' (Hartzmark, 1991) establish larger long positions when they anticipate higher excess returns. To compute each investor's big hit forecasting ability time-series, we perform the following times-series regression for each investor in each month respectively:

$$R_{i,j} = \alpha + \beta_{i,t} D_{i,j} + \varepsilon_{i,j}. \tag{2}$$

At the beginning of month t, the subsequent 1-month risk-adjusted excess return $R_{i,j}$ of each of investor i's previous stock purchases j completed at least 20 trading days before t are regressed on the purchases' respective dollar amounts $D_{i,j}$ (i.e., the number of shares multiplied by the transaction share price). Using the estimated $\hat{\beta}_{i,t}$ coefficient and the probability significance level from the hypothesis test that this coefficient equals zero, we follow Hartzmark (1991) and define individual i's big hit forecasting ability as of month t as

$$FB_{i,t} = (1 - \textit{probability significance level}_{i,t}) \times (\textit{sign of } \beta_{i,t}). \tag{3}$$

The range ($-1 \leqslant FB_{i,t} \leqslant 1$) encompasses the universe of investors: those with statistically significant inferior ability (when $FB_{i,t}$ is close to -1), those with weak ability (when $FB_{i,t}$ is close to 0), and those with statistically significant superior ability (when $FB_{i,t}$ is close to 1).

We again provide a numeric example to aid in the interpretation of this second ability proxy. Suppose that in a given month, an investor's $\hat{\beta}_{i,t}$ equals 3.0 (implying a positive relation between the dollar values of the investor's previous purchases and their subsequent returns) and its associated probability significance level is 0.05, implying that the null hypothesis of no relation between purchase dollar value and subsequent excess return (i.e., that $\beta_{i,t} = 0$) can be rejected with 95 percent confidence. In this case, $FB_{i,t} = (1 - 0.05) \times 1 = 0.95$, indicating precision in the investor's private signals regarding both the signs and magnitudes of previous purchases' subsequent excess returns. Once more, positive (negative) measures generally suggest superior (inferior) ability or signal precision.

Panel C of Table 1 reports summary statistics for the two ability measures. Given that the mean and median consistent (big hit) abilities are both significantly negative (economically insignificant), it seems apparent that individuals, on average, do not possess forecasting ability. In other words, their private signals are not precise. The two ability measures are weakly positively correlated with each other (coefficient of correlation = 0.13) and with the previous month's portfolio return (coefficient of correlation = 0.08). The next section of the paper will focus on whether the temporal variation in perceived private signal precision—for which the ability measures proxy—influences individuals' future purchase quality and trading tendencies.

3.2. Interaction between performance and trading

As discussed, if more precise private signals enable traders to make wiser purchase decisions, then persistent precision would imply a positive relation between demonstrated forecasting ability and future trade quality. To investigate whether perceived private signal precision is linked to the performance of future trades, we adopt two alternative regression specifications. We first perform a Probit regression to test the hypothesis that as an investor's previous trading ability (proxying for the perceived precision of prior private signals) improves, so does the probability that the investor's next purchase will be profitable. In particular, the dependent variable equals 1 if the next stock purchased by a household after inferring its ability on a monthly basis subsequently generates a positive abnormal 1-month return; 0 otherwise. The regression's independent variables include investor fixed effects, as well as investors' (i) perceived private signal precision proxy, $FS_{i,t}$ or $FB_{i,t}$ in the period; (ii) past-month portfolio return; and (iii) past-6-month portfolio return. In addition, we also perform a linear regression to test the hypothesis that as an investor's perceived private signal precision increases, so does the profitable portion of the investor's future purchases. We exclude an observation if the household makes no purchase trade in the next 6 months. Consistent with the above trade profitability definition, the dependent variable equals the fraction of purchases executed by a household during the 6 months following private signal precision inference which subsequently generate 1-month abnormal returns.

In Table 2, which reports the results of the two regression specifications, the significantly positive proxy coefficients in both models lend support to the predictability of inferred signal precision on future purchases' performance. Looking at the Probit model, marginal effect analysis indicates that an improvement in the forecasting ability proxies from zero to one (i.e., from signals which are perceived to be non-informative to perfectly accurate) increases the probability that the next purchase will be profitable by 14–16 percent. The linear model generates similar results, in that the same improvement will increase the fraction of future profitable purchases by 4–5 percentages.

This evidence that higher inferred signal precision improves future purchases' performance leads us to next study whether investors condition their future trading intensity on their inferred private signal precision (controlling for other variables that may affect stock trading tendencies) using the following fixed effect regression in Table 3:

$$\begin{aligned} T_{i,t} = {} & c_i + \rho_1 F_{i,t} + \rho_2 N_{i,t} + \rho_3 T^{*}_{i,t-1} + \rho_4 R_{m,t-1} + \rho_5 R_{i,t-1} + \rho_6 P_{i,t-1} \\ & + \rho_7 (SD_{m,t} - SD_{m,t-1}) + \rho_8\, GR3_{m,t-1} + \rho_9 V_{m,t-1} + \rho_{10}\, DEC_t + \rho_{11}\, JAN_t + \varepsilon_{i,t}. \end{aligned} \tag{4}$$

In Panel A of Table 3, the dependent variable $T_{i,t}$ equals the number of household i's month t total trades (purchases and sales) in the first two columns, the household's monthly purchases in the middle two columns, and the household's monthly sales in the

Table 2
Inferred ability and profitability of future trades

For the Probit model, the dependent variable equals 1 if the next stock purchased by a household after inferring its ability subsequently generates a positive abnormal 1-month return; and 0 otherwise. For the linear model, the dependent variable equals the fraction of stocks purchased during the 6 months following the household's ability inference that generate positive subsequent 1-month abnormal returns. Independent variables include individual fixed effects, the investor's (i) inferred ability monthly measure: $FS_{i,t}$ or $FB_{i,t}$; (ii) lagged 1-month portfolio return; (iii) lagged 6-month portfolio return; and (iv) the total number of purchases executed by the investor over the 6 months following their ability inference. * (**) Indicates statistical significance at the 5% (1%) level. *t*-Statistics are provided in brackets.

	FS		*FB*	
	Probit model	Linear model	Probit model	Linear model
Inferred ability	**0.165	**0.045	**0.139	*0.042
	[4.12]	[2.89]	[3.24]	[2.29]
Lagged 1-month portfolio return	0.012	0.009	0.014	0.011
	[1.33]	[0.85]	[1.15]	[0.41]
Lagged 6-month portfolio return	0.002	0.004	0.002	0.003
	[0.79]	[0.92]	[0.37]	[0.42]
Individual fixed effect	Yes	Yes	Yes	Yes
(Pseudo) R-square	0.19	0.04	0.14	0.04
N	52,642	52,642	52,642	52,642

last two columns. In Table 3 Panel B, the dependent variable is household i's month t average portfolio turnover in the first two columns, the household's monthly purchase portfolio turnover in the middle two columns, and the household's monthly sale portfolio turnover in the last two columns.[8]

Turning towards the regressors, the independent variable of interest ($F_{i,t}$) assumes the value of $FS_{i,t}$ and $FB_{i,t}$, respectively. Positing that the link between perceived signal accuracy and future trade performance will lead learning investors with superior perceived signal accuracy to trade more aggressively, we expect a positive ρ_1. Next, we add two variables to control for correlation within the model. Namely, we include $N_{i,t}$ to control for correlation between the dependent variable and the number of previous purchases to date, while $T_{i,t-1}$ controls for potential serial correlation in the dependent variables. However, to mitigate any parameter estimation bias due to the inclusion of the lagged dependent variable as a regressor, we follow Holtz-Eakin, Newey, and Rosen (1988)'s instrumental variable approach and replace lagged turnover with the fitted value $T^*_{i,t-1}$ from the following regression:

$$T_{i,t-1} = a + b_1 T_{i,t-2} + b_2 T_{i,t-3} + b_3 T_{i,t-4} + e_{i,t}. \tag{5}$$

We also include additional explanatory variables to control for other trading needs. For example, we include the previous month's S&P500 index return ($R_{m,t-1}$) to account for the fact that individuals' trading decisions are influenced by the previous month's market return (Barber, Odean, and Zhu, 2007a). Including lagged long-run market performance ($GR3_{m,t-1}$), the S&P500 return cumulated over the past 3 years, helps capture possible trading behavior evolution, such as changing/persistent investor sentiment. To distinguish

[8]In unreported analyses, we replicate the regressions using quarterly turnover and obtain similar results.

Table 3
Security analysis ability and stock purchases

We perform the following fixed-effect panel regression specification:

$$T_{i,t} = c_i + \rho_1 F_{i,t} + \rho_2 N_{i,t} + \rho_3 T^{*}_{i,t-1} + \rho_4 R_{m,t-1} + \rho_5 R_{i,t-1} + \rho_6 P_{i,t-1} + \rho_7 (SD_{m,t} - SD_{m,t-1}) + \rho_8\, GR3_{m,t-1} + \rho_9 V_{m,t-1} + \rho_{10}\, DEC_t + \rho_{11}\, JAN_t + \varepsilon_{i,t}.$$

In Panel A, the dependent variable $T_{i,t}$ equals the number of household I's month t total trades (purchases and sales) in the first two columns, the household's monthly purchases in the middle two columns, and the household's monthly sales in the last two columns. In Panel B, the dependent variable $T_{i,t}$ equals household i's average portfolio turnover during month t in the first two columns, the household's monthly purchase portfolio turnover in the middle two columns, and the household's monthly sale portfolio turnover in the last two columns.

$F_{i,t}$ assumes the value of $FS_{i,t}$ and $FB_{i,t}$, respectively. $FS_{i,t}$ ($FB_{i,t}$) measures investors' ability to forecast the signs (both the signs and magnitudes) of excess stock returns over the following month. $N_{i,t}$ is the number of purchases the investor has performed to date, a component of the $FS_{i,t}$ determination. To obtain the next regressor ($T^{*}_{i,t-1}$), the fitted value of the lagged dependent variable $T_{i,t-1}$, we apply the instrumental variable approach to the regression: $T_{i,t-1} = a + b_1 T_{i,t-2} + b_2 T_{i,t-3} + b_3 T_{i,t-4} + e_{i,t}$. We also include lagged market return $R_{m,t-1}$, lagged portfolio return $R_{i,t-1}$, households' lagged mutual fund and stock positions $P_{i,t-1}$ (coefficients and standard errors are multiplied by 1,000,000), change in the cross-sectional stock return standard deviation $SD_{m,t}-SD_{m,t-1}$, lagged 3-year S&P500 return $GR3_{m,t-1}$, lagged dollar value of NYSE/AMEX/NASDAQ traded stocks $V_{m,t-1}$, and December DEC_i and January JAN_i dummy variables.

There are 65,118 observations for each regression. Coefficients and t-statistics are reported below. * (**) Indicates statistical significance at the 5% (1%) level. t-Statistics are reported in brackets.

Panel A: Number of trades

	Total trades		Purchase trades		Sale trades	
	$FS_{i,t}$	$FB_{i,t}$	$FS_{i,t}$	$FB_{i,t}$	$FS_{i,t}$	$FB_{i,t}$
Inferred ability	**0.045	**0.044	**0.064	**0.051	0.020	*0.031
	[2.98]	[3.02]	[3.25]	[3.11]	[1.10]	[1.97]
Total prior purchases	0.094	0.087	0.082	0.080	0.056	0.057
	[0.89]	[1.05]	[1.43]	[1.51]	[0.73]	[0.75]
Lag (Trade, fitted)	**0.204	**0.195	**0.164	**0.156	**0.135	**0.140
	[67.44]	[59.49]	[55.67]	[61.42]	[33.49]	[37.53]
Lag (Market Ret)	**0.910	**0.893	**0.805	**0.809	**0.551	*0.575
	[4.98]	[4.94]	[4.31]	[4.30]	[2.61]	[2.36]
Lag (Portfolio Ret)	**0.223	**0.196	**0.321	**0.286	**0.177	**0.182
	[3.59]	[3.74]	[2.86]	[2.64]	[3.40]	[3.35]
Lag (Position)	**0.149	**0.146	**0.147	**0.144	0.151	0.151
	[4.94]	[4.85]	[4.27]	[4.22]	[1.80]	[1.89]
Change in Std. Dev.	−0.104	−0.114	**−0.383	**−0.364	0.008	0.014
	[−1.45]	[−1.92]	[−3.29]	[−3.05]	[0.81]	[1.06]
Lag (3-year Ret)	**0.446	**0.477	**0.424	**0.421	**0.582	**0.583
	[8.96]	[8.23]	[4.15]	[4.11]	[8.05]	[7.65]
Lag (Trading Vol.)	**0.544	**0.537	**0.498	**0.505	*0.296	*0.307
	[10.61]	[10.59]	[9.99]	[9.92]	[2.22]	[2.46]
December dummy	−0.011	−0.010	−0.025	−0.027	−0.018	−0.018
	[−0.89]	[−0.87]	[−1.61]	[−1.58]	[−0.59]	[−0.56]

Table 3 (*continued*)

Panel A: Number of trades

	Total trades		Purchase trades		Sale trades	
	$FS_{i,t}$	$FB_{i,t}$	$FS_{i,t}$	$FB_{i,t}$	$FS_{i,t}$	$FB_{i,t}$
January dummy	0.035	0.036	*0.045	*0.044	0.028	0.026
	[1.87]	[1.69]	[2.34]	[2.29]	[1.01]	[1.01]

Panel B: Turnover

	Whole sample		Purchase turnover		Sale turnover	
	$FS_{i,t}$	$FB_{i,t}$	$FS_{i,t}$	$FB_{i,t}$	$FS_{i,t}$	$FB_{i,t}$
Inferred ability	**0.022	**0.018	**0.018	*0.016	*0.006	*0.007
	[5.74]	[3.33]	[6.84]	[2.30]	[1.98]	[2.11]
Total prior purchases	−0.007	−0.006	−0.010	−0.008	−0.006	−0.005
	[−0.93]	[−0.75]	[−1.05]	[−0.81]	[−0.64]	[−0.44]
Lag (Turnover, fitted)	**0.069	**0.062	**0.077	**0.075	**0.039	**0.042
	[15.28]	[14.77]	[28.93]	[29.42]	[11.22]	[9.74]
Lag (Market Ret)	**0.183	**0.189	**0.162	**0.165	**0.079	**0.079
	[4.84]	[5.15]	[6.30]	[6.34]	[2.70]	[2.65]
Lag (Portfolio Ret)	**0.047	**0.048	**0.019	**0.019	**0.043	**0.044
	[6.85]	[7.04]	[3.94]	[3.95]	[7.55]	[7.49]
Lag (Position)	−0.001	0.006	**−0.001	**−0.001	**0.001	**0.001
	[−0.05]	[0.27]	[−4.87]	[−4.96]	[4.92]	[4.87]
Change in Std. Dev.	**0.084	**0.091	*0.032	*0.032	**0.094	**0.097
	[4.00]	[4.54]	[2.12]	[2.05]	[5.32]	[5.65]
Lag (3-year Ret)	**0.173	**0.149	**0.112	**0.112	**0.094	**0.092
	[16.98]	[16.22]	[16.04]	[15.88]	[11.37]	[10.94]
Lag (Trading Vol.)	**−0.002	**−0.002	**−0.002	**−0.002	**−0.001	**−0.002
	[−16.43]	[−15.51]	[−16.24]	[−16.83]	[−6.94]	[−7.17]
December dummy	*−0.006	*−0.006	*−0.004	**−0.006	−0.004	−0.004
	[−2.45]	[−2.31]	[−2.44]	[−2.79]	[−1.49]	[−1.51]
January dummy	**0.012	**0.011	0.004	0.004	**0.009	**0.011
	[3.21]	[2.86]	[1.64]	[1.79]	[2.87]	[3.12]

between trades motivated by return-feedback rather than inferred ability, we also include investors' lagged personal portfolio monthly returns, $R_{i,t-1}$. For example, regardless of forecasting ability, individuals prone to the disposition effect who experience superior returns are more likely to increase their trading (i.e., sell their winners and use the resulting proceeds to purchase more shares).[9] Further, because cash-strapped investors may stop

[9]While perceived private signal precision and past performance measures are correlated, our results show both to be statistically significant; thus multicollinearity does not prevent us from identifying their significance separately.

trading simply because they have lost most of their investment and have no more money with which to trade, we include the market value of an investor's stock and mutual fund portfolio at the end of the previous month, $P_{i,t-1}$.

Next, to control for rational portfolio rebalancing trading, we use the change in cross-sectional return standard deviation for all stocks in the market, $SD_{m,t}-SD_{m,t-1}$, as a proxy for the change in the covariance of stock returns, where $SD_{m,t}$ is the cross-sectional return standard deviation of all stocks in the market. We also include the dollar value of lagged NYSE/AMEX/NASDAQ market trading volume, $V_{m,t-1}$, to control for investment fads and/or herding. Furthermore, we use both December and January dummies, DEC_t and JAN_t, respectively, to capture possible trading seasonality and tax considerations (see, e.g., Kumar and Lee, 2006). Finally, we include a unique intercept for each individual in order to capture trading associated with latent variables' time-invariant components such as an investor's risk attitude, gender, personal income, education, etc. In other words, this "fixed effect" adjustment—which controls for each investor's average perceived private signal precision—guarantees that ρ_1 will reflect only the temporal relation between perceived private signal precision and trading tendency.

Panel A of Table 3 reveals that, as predicted, the regressions produce significantly positive estimated $FS_{i,t}$ and $FB_{i,t}$ coefficients (except for $FS_{i,t}$'s inability to affect future sales).[10] Controlling for other variables, as an investor's perceived private signal precision improves from perfectly uninformative to perfectly informative, the investor's subsequent monthly trades/purchases/sales increase by 0.03–0.06 transactions. Hence, we reject the null hypothesis that investors' future stock trading is unaffected by the inferred accuracy of their private signals. The positive ability coefficients in both Tables 2 and 3 are consistent with investor learning: private signal precision boosts future trade profitability, which in turn spurs individuals to trade more aggressively.

A few results regarding the control variable coefficients merit discussion. First, as would be expected, the lagged dependent variable coefficient is positive and highly significant, suggesting temporal persistence in investors' trade tendencies. Second, previous raw performance measures impact individuals' trading decisions. Consistent with Gervais and Odean (2001) and Investment Company Institute (2003), we find that investors' trade frequency increases with both short-term and long-term historical market portfolio returns (i.e., $R_{m,t-1}$ and $GR3_{m,t-1}$, respectively). Further, investors' past personal portfolio performance also influences their trading. While previous raw portfolio returns are correlated with perceived private signal precision (which depend on previous purchases' subsequent 1-month excess returns), it is important to remember that the former is impacted by current market performance, factor exposure, and returns of holdings purchased more than 1-month prior (none of which would affect the latter). Overall, our main findings remain robust even after including these control variables.

The main results presented in Panel B mirror those described in Panel A—i.e., the forecasting ability proxies are once more significantly positive. Controlling for other variables, as an investor's perceived private signal precision improves from perfectly uninformative to perfectly informative, the investor's subsequent monthly turnover increases by 0.6–2.2 percent (or by 7–26 percent on an annual basis). It should be noted that learning (as measured by the private signal precision proxy coefficients) has the weakest impact on sale turnover, suggesting that private signal precision better facilitates

[10] All statistics are calculated using White-heteroscedasticity consistent variance–covariance matrices.

purchase decisions, which require a much more costly search than sale decisions. Overall, we again reject the null hypothesis that investors' future stock trading is unaffected by the inferred accuracy of their private signals.

4. Trading experience and performance

Being that trading ability proxies for past private signal precision are positively linked to future trade profitability and intensity, we next hypothesize that trading experience will enable individuals to more accurately infer their private signal precision, and the resulting increased future trade profitability implication will lead learning individuals to accordingly adjust their trading behavior and thus enhance their overall investment performance. We test the null hypothesis—i.e., that trading experience does not affect investors' future performance—under two frameworks.

First, we examine whether an investor's excess portfolio return improves as the investor gains trading experience by performing the following fixed effects linear regression:

$$RER_{i,t} = C_i + \rho_1\, Purchases_{i,t} + \rho_2\, Stocks_{i,t} + \rho_3\, Variance_{i,t} + \rho_4\, Time_{i,t} + \theta'\, Controls_{i,t} + \varepsilon_{i,t} \tag{6}$$

Looking at the dependent variable in Eq. (6), each investor's risk-adjusted excess portfolio return time series ($RER_{i,t}$) equals the sum of the estimated intercept and residuals from a regression of the investor's monthly raw portfolio returns net the Treasury-bill rates on the Fama-French factors. Next, four different measures are used to proxy for investor i's trading experience as of the beginning of month t. First, recalling Eq. (1), since an investor's capability to infer her private signal precision should increase as she purchases more and new stocks, $Purchases_{i,t}$ equals the total number of stock purchases the investor has previously completed, while $Stocks_{i,t}$ equals the total number of different stocks the investor has previously purchased. Additionally, it is straightforward from Eq. (2) that as the variance ($Variance_{i,t}$) of these previous purchases' dollar amounts increases, the more accurately big hit ability $FB_{i,t}$ can be estimated. Furthermore, given that it seems plausible that an investor with longer account tenure has had more opportunities to infer her private signal precision, $Time_{i,t}$ equals the number of months which have elapsed since the opening of the investor's oldest account. Positive coefficients for the experience measures would be consistent with the existence of effective investor learning. Finally, also included in Eq. (6) is a vector of control variables ($Controls_{i,t}$) which contains 11-month dummies, the investor's previous month's portfolio value, and the current and lagged value of the market's monthly trading volume (to control for possible herding and changing investor sentiment).

In Table 4 Panel A, five versions of Eq. (6) regression are applied to all sample investors. The first four regression specifications sequentially consider the investor experience measures, while the fifth specification includes all four experience measures simultaneously. While neither $Purchases_{i,t}$ nor $Stocks_{i,t}$ significantly impact future portfolio excess return, the statistically significant $Variance_{i,t}$ and $Time_{i,t}$ coefficients (specifications III through V) reject the null hypothesis that these latter two experience proxies do no improve investment performance.

In Panel B, the fifth regression specification containing all four experience proxies is performed using different investor sub-samples: active traders and inactive traders; and

Table 4
Trading experience and portfolio performance

This table reports the results of fixed effect panel regressions which test whether investors' previous trading experience improves their future risk-adjusted excess portfolio return.

$$RER_{i,t} = C_i + \rho_1\, Purchases_{i,t} + \rho_2\, Stocks_{i,t} + \rho_3\, Variance_{i,t} + \rho_4\, Time_{i,t} + \theta'\, Controls_{i,t} + \varepsilon_{i,t}$$

For household i in month t, $RER_{i,t}$ is the Fama-French three-factor adjusted excess portfolio return; $Purchases_{i,t}$ is the number of previous purchases the investor has made; $Stocks_{i,t}$ is the number of different stocks the investor has previously purchased; $Variance_{i,t}$ is the variance of these previous purchases' dollar amounts, and $Time_{i,t}$ denotes the number of months which have elapsed since account opening. $Controls_{i,t}$ is a vector of control variables, including 11-month dummies, the investor's previous month's portfolio value, and the current and lagged value of the market's monthly trading volume.

While all sample households are included in Panel A regressions, Panel B regressions are performed on only a portion of sample investors. Specifically, Active traders complete at least 25 trades in the sample period; Inactive traders complete fewer than 25 trades. Winners include households belonging to the top tercile of investors sorted on average excess portfolio return; Average performers include those belonging to the middle tercile; Losers include those belonging to the bottom tercile.

Coefficients are multiplied by 1,000,000 and are accompanied by * (**) if significant at the 5% (1%) level. *t*-Statistics are provided in brackets.

Panel A. Full sample regressions

	Specification I	Specification II	Specification III	Specification IV	Specification V
Purchases	−37.863				−0.709
	[−0.87]				[−0.01]
Stocks		−91.395			−304.705
		[−0.88]			[−1.37]
Variance			*1.154E−5		*0.000
			[2.39]		[2.33]
Time				**545.903	**608.429
				[6.52]	[6.98]
R-square	0.0163	0.0163	0.0164	0.0170	0.0172
N	65,118	65,118	65,118	65,118	65,118

Panel B: Subsample regressions for specification V

	Active traders	Inactive traders	Winners	Average	Losers
Purchases	−26.095	−150.643	−76.496	167.953	−13.226
	[−0.26]	[−0.14]	[−0.39]	[1.33]	[−0.07]
Stocks	−213.682	−1542.711	−167.217	**−683.423	−237.693
	[−0.87]	[−1.07]	[−0.38]	[−2.74]	[−0.36]
Variance	1.087E−5	1.201E−5	1.324E−5	−1.981E−6	1.104E−5
	[1.93]	[1.02]	[1.56]	[−0.21]	[1.20]
Time	**426.923	**899.080	200.522	**668.041	**997.368
	[3.35]	[7.11]	[0.92]	[8.10]	[5.80]
R-square	0.0163	0.0197	0.0148	0.0366	0.0182
N	33,718	31,400	19,476	26,655	18,987

winners, average performers, and losers. Active traders complete at least 25 trades in the sample period, whereas inactive traders complete fewer than 25 trades. Winners include households belonging to the top tercile of investors sorted on average excess portfolio return; Average performers include those belonging to the middle tercile; Losers include those belonging to the bottom tercile. Looking at the sub-sample results, $Time_{i,t}$ is the only experience measure that is significant across most different pools of investors (i.e., each sub-sample except for winners). $Time_{i,t}$'s stronger impact on inactive traders and investors with average or below average portfolio performance suggests that experience may be a more successful deterrent than inducement. In other words, the response experienced individuals have when learning about their private signal precision may be asymmetric. Specifically, in order to achieve higher portfolio returns, investors with inferior ability may be more inclined to decrease their future trade intensity than investors with superior ability are inclined to increase their future trade intensity.

Our second approach to analyzing whether experience helps improve investment performance is to directly assess the quality of investors' trade decisions. Despite previous studies which have found that individuals on average make poor decisions (e.g., Barber and Odean, 2000; Barber, Odean, and Zhu, 2007a), it seems reasonable to expect trade quality to improve with investment experience. Accordingly, we next adopt a calendar-time return methodology (Barber and Lyon, 1997; Odean, 1999) to consider how one measure of trade quality (i.e., the extent to which purchases subsequently outperform sales) varies with investment experience.

We begin this examination by partitioning sample transactions into more- and less-experienced sub-samples (we consider two classification rules, discussed below). We then form portfolios that essentially mimic the two experience sub-samples' buying and selling decisions. That is, a purchase (sale) transaction in the experienced sub-sample prompts the experienced purchase (sale) portfolio to buy and hold the stock for 1 month.[11] Likewise, a purchase (sale) transaction in the inexperienced sub-sample prompts the inexperienced purchase (sale) portfolio to buy and hold the stock for 1 month. The daily raw returns of the four resulting portfolios (i.e., experienced purchases, experienced sales, inexperienced purchases, and inexperienced sales) are calculated on both an equally-weighted and value-weighted basis. Next, average trade quality *within* a given experience sub-sample can be approximated by (i) comparing the daily raw returns of its purchase and sale portfolios, and (ii) regressing this net return series on the Fama-French factors to estimate excess return. For example, if (i) the experienced purchase (sale) portfolio's average subsequent raw returns exceed those of the experienced sale (purchase) portfolio, or (ii) the average experienced buy-minus-sell excess return alpha is significantly positive (negative), then the experienced sub-sample can be said to have made high (low) quality trades. Further, by comparing the average buy-minus-sell daily raw and excess returns *across* the two experience sub-samples, we can determine whether experience helps improve trade quality.

In Table 5, transactions occurring earlier (later) in the sample period—i.e., between 1991 and 1993 (1994 and 1996)—are assigned to the less- (more-) experienced sub-sample. Looking at the daily return differences between purchase and sale portfolios *within* these sub-samples, it initially appears that the average individual investor is not a very good trader (supporting Odean, 1999; Barber and Odean, 2000). That is, both the inexperienced

[11]This assumption is largely to be consistent with the 1-month period used in the rest of the paper. We also assume 1-year holding periods and obtain slightly stronger results.

Table 5
Calendar-time return differences between periods of varying experience: full sample

This table contrasts calendar-time returns for trades made by sample investors across periods with varying experience. Specifically, the less-experienced period spans 1991–1993, while the more-experienced period spans 1994–1996. The mimicking purchase (sale) portfolio purchases a stock when sample investors purchase (sell) the stock. Returns assume a 1-month holding period. Value-weighted portfolio returns are weighted by the dollar value of each investor trade. The three-factor alpha is obtained by regressing the daily spread between the purchase and sale portfolios on the Fama-French factors (Market, SMB, HML). *, **, And *** indicate statistical significance at the 10, 5, and 1 percent level, respectively. *t*-Statistics are enclosed in brackets.

	Daily purchase return	Daily sales return	Daily return difference	3-Factor alpha
Panel A: Value-weighted mimicking portfolios				
Less experienced				
Mean (1)	0.029	0.068	**−0.038	***−0.036
t-Statistic	[0.78]	[1.83]	[−22.22]	[−20.69]
More experienced				
Mean (2)	0.044	0.051	***−0.006	***−0.014
t-Statistic	[0.91]	[1.12]	[−3.75]	[−8.38]
Difference (2−1)	0.015	−0.017	***0.032	***0.022
t-Statistic	[0.24]	[−0.29]	[13.67]	[9.15]
Panel B: Equally-weighted mimicking portfolios				
Less experienced				
Mean (1)	0.031	**0.066	***−0.035	***−0.035
t-Statistic	[0.87]	[2.86]	[−21.88]	[−21.89]
More experienced				
Mean (2)	0.042	*0.059	***−0.017	***−0.027
t-Statistic	[1.08]	[1.71]	[−12.14]	[−16.88]
Difference (2−1)	0.012	−0.007	***0.018	***0.008
t-Statistic	[0.22]	[−0.16]	[8.47]	[3.53]

and experienced sub-samples' value-weighted purchase portfolios significantly underperform their respective sale portfolios (by 3.8 and 0.6 basis points per day, respectively). However, this 3.2 basis point difference in net portfolio performance *between* sub-samples is statistically significant, suggesting that relative trade quality does indeed increase with experience. Additionally, while the average daily excess returns of both the inexperienced and experienced sub-samples' buy-minus-sell trading strategies are significantly negative (by 3.6 and 1.4 basis points per day, respectively), the 2.2 basis point improvement *between* the experienced and inexperienced three-factor alphas lends additional support to our argument. We obtain similar results when the subsequent daily returns of the experienced and inexperienced purchase and sale portfolios are calculated on an equally-weighted basis.

However, to determine whether this average relative trade performance improvement results from experience (i) enabling investors to increase their trade quality (i.e., investors learn to trade better), or (ii) instructing investors as to appropriate market presence (i.e., poorly-performing investors quit trading, see Seru, Shumway, and Stoffman, 2007), we replicate the above portfolio approach using only investors who trade in both sub-periods. Looking at the results in Table 6, we find again that relative trade performance

Table 6
Calendar-time return differences between periods of varying experience: sub-sample

This table replicates Table 5, using only the 1,854 sample households that made at least one trade during both the less-experienced sub-period (1991–1993) and the more-experienced sub-period (1994–1996). Again, the mimicking purchase (sale) portfolio purchases a stock when sample investors purchase (sell) the stock. Returns assume a 1-month holding period. Value-weighted portfolio returns are weighted by the dollar value of each investor trade. The three-factor alpha is obtained by regressing the daily spread between the purchase and sale portfolios on the Fama-French factors (Market, SMB, HML). *, **, And *** indicate statistical significance at the 10, 5, and 1 percent level, respectively. t-Statistics are enclosed in brackets.

	Daily purchase return	Daily sales return	Daily return difference	3-Factor alpha
Panel A: Value-weighted mimicking portfolios				
Less experienced				
Mean (1)	0.035	0.072	***−0.037	***−0.044
t-Statistic	[0.87]	[1.87]	[−21.76]	[−25.88]
More experienced				
Mean (2)	0.044	0.051	***−0.006	***−0.010
t-Statistic	[0.91]	[1.12]	[−3.75]	[−8.38]
Difference (2−1)	0.009	−0.021	*0.031	**0.034
t-Statistic	[0.14]	[−0.35]	[1.87]	[2.18]
Panel B: Equally-weighted mimicking portfolios				
Less experienced				
Mean (1)	0.038	*0.069	**−0.031	***−0.033
t-Statistic	[0.92]	[1.73]	[−18.41]	[−20.59]
More experienced				
Mean (2)	0.042	*0.059	***−0.017	***−0.027
t-Statistic	[1.08]	[1.71]	[−12.14]	[−16.88]
Difference (2−1)	0.005	−0.010	***0.014	**0.006
t-Statistic	[0.08]	[−0.19]	[6.49]	[2.57]

improves significantly with experience, albeit to a lesser extent, when considering only investors who stay in the market. This suggests that the overall performance improvement in the second half of the sample period is due to both sample selection and increased trading ability. Nevertheless, while the extent to which their purchases underperform their sales may have decreased, it is important to bear in mind that these more-experienced individuals still, on average, cannot beat the market.

Finally, by comparing trades executed in different calendar time periods (as we do in Tables 5 and 6), we ignore the possibility that unobserved variables might systematically affect all investors in both sub-periods (e.g., a temporal shift in investor sentiment or market return), first depressing and then boosting relative trade quality. To circumvent this problem and compare the subsequent investment performance of trades made in the same time period by investors with varying investment experience, we adopt an alternate method for separating experienced from inexperienced trades. Specifically, in Table 7, transactions performed by investors with newer (older) accounts—i.e., those opened in 1990 or 1991 (between 1985 and 1989)—are assigned to the less- (more-) experienced sub-sample.[12]

[12]We exclude households who opened their first account prior to 1985 primarily because these households tend to include much older and wealthier individuals, and previous studies have shown that such characteristics

Table 7
Calendar-time return differences between investors with varying experience

This table contrasts calendar-time returns for trades made in the same period (525,139 trades between 1992 and 1996) by sample investors with varying experience. Specifically, the less-experienced investors opened their accounts in 1990 or 1991 ($n = 18,374$), while the more-experienced investors opened their accounts between 1985 and 1989 ($n = 37,771$). The mimicking purchase (sale) portfolio purchases a stock when sample investors purchase (sell) the stock. Returns assume a 1-month holding period. Value-weighted portfolio returns are weighted by the dollar value of each investor trade. The three-factor alpha is obtained by regressing the daily spread between the purchase and sale portfolios on the Fama-French factors (Market, SMB, HML). *, **, And *** indicate statistical significance at the 10, 5, and 1 percent level, respectively. t-Statistics are enclosed in brackets.

	Daily purchase return	Daily sales return	Daily return difference	3-Factor alpha
Panel A: Value-weighted mimicking portfolios				
Less experienced				
Mean (1)	0.042	*0.070	***−0.028	***−0.033
t-Statistic	[1.07]	[1.79]	[−3.90]	[−4.13]
More experienced				
Mean (2)	*0.065	**0.071	−0.006	−0.010
t-Statistic	[1.87]	[2.03]	[−0.89]	[−1.43]
Difference (2−1)	0.024	0.0014	**0.022	**0.023
t-Statistic	[0.45]	[0.03]	[2.30]	[2.16]
Panel B: Equally-weighted mimicking portfolios				
Less experienced				
Mean (1)	0.042	*0.068	***−0.026	***−0.029
t-Statistic	[1.14]	[1.84]	[−4.21]	[−4.13]
More experienced				
Mean (2)	*0.066	*0.069	−0.004	−0.009
t-Statistic	[1.94]	[1.92]	[−0.59]	[−1.29]
Difference (2−1)	0.024	0.002	**0.022	**0.02
t-Statistic	[0.47]	[0.04]	[2.42]	[2.02]

This change in experience classification, which compares the same-period returns of different investor groups, produces two notable results. First, while both the inexperienced and experienced sub-samples' mimicking purchase portfolios still underperform their respective sale portfolios (by 2.8 and 0.6 basis points per day, respectively, when portfolio returns are value-weighted), the experienced return difference is no longer statistically significant. Second, while the average daily excess returns of both the inexperienced and experienced sub-samples' buy-minus-sell trading strategies are still negative (by 3.3 and 1.0 basis points per day, respectively), the experienced excess return is similarly no longer statistically different from zero, suggesting relatively better performance by the experienced group. Thus, the significant improvement in the raw and excess return differences between sub-samples appears to be driven by the remarkably poor quality of inexperienced investors' trades. We obtain similar results when the subsequent daily

(*footnote continued*)
considerably affect trade decisions and performance (Dhar and Zhu, 2006; Linnainmaa, 2006; Grinblatt and Keloharju, 2001).

returns of the experienced and inexperienced purchase and sale portfolios are calculated on an equally-weighted basis.

5. Conclusions

This paper analyzes potential learning behavior evidenced by individual investors' stock trading from two perspectives. First, we question whether investors' future trade performance and activity is affected by their previously-demonstrated trading ability, which proxies for private signal precision and is inferred from their prior purchases' subsequent performance. We find that (i) the subsequent purchase's profit likelihood, (ii) the profitable portion of ensuing purchases, and (iii) future trade intensity measures all increase with our proxies for perceived private signal precision. Together, this suggests that as an investor's confidence in the precision in her private signals increases, the resulting indication of higher future purchase excess returns spurs the investor to trade more actively.

Second, we question whether trading experience help investors obtain better investment performance. Not only does excess portfolio return improve with account tenure, but we also find that trade quality (i.e., average raw and excess buy-minus-sell returns) significantly increases with experience (i.e., calendar time and account tenure). Overall, our findings are consistent with the hypothesis that despite their various documented mistakes, individual investors do learn from their investment history, adjust their future stock trading accordingly, and achieve higher investment performance as they gain experience.

References

Barber, Brad M., Lyon, John, 1997. Detecting long-run abnormal stock returns: the empirical power and specification of test-statistics. Journal of Financial Economics 43 (3), 341–372.

Barber, Brad M., Odean, Terrance, 2000. Trading is hazardous to your wealth: the common stock investment performance of individual investors. Journal of Finance 55 (2), 773–806.

Barber, Brad M., Odean, Terrance, Zhu, Ning, 2007a. Systematic noise. Journal of Financial Markets, forthcoming.

Barber, Brad M., Odean, Terrance, Zhu, Ning, 2007b. Do noise traders move the markets. Review of Financial Studies, forthcoming.

Becker, Connie, Myers, David, Schill, Michael, 1999. Conditional market timing with benchmark investors. Journal of Financial Economics 52 (1), 119–148.

Camerer, Colin, Hogarth, Robin M., 1999. The effects of financial incentives in experiments: a review and capital-labor-production framework. Journal of Risk and Uncertainty 19 (1-3), 7–42.

Coursey, DonL., Hovis, John L., Schulze, William D., 1987. The disparity between willingness to accept and willingness to pay measures of value. Quarterly Journal of Economics 102 (3), 679–690.

Cumby, Robert E., Modest, David M., 1987. Testing for market timing ability: a framework for forecast evaluation. Journal of Financial Economics 19 (1), 169–189.

Daniel, Kent, Hirshleifer, David, Subrahmanyam, Avanidhar, 1998. Investor psychology and security market under- and overreactions. Journal of Finance 53 (6), 1839–1886.

Dhar, Ravi, Zhu, Ning, 2006. Up close and personal: an individual level analysis of the disposition effect. Management Science 52 (5), 726–740.

Dhar, Ravi, Goetzmann, William, Sheperd, Shane, Zhu, Ning, 2004. The impact of clientele change, evidence from stock splits. Yale School of Management working paper, pp. 1–58.

Erev, Ido., Roth, Alvin E., 1998. Predicting how people may play games: reinforcement learning in experimental games with unique, mixed strategy equilibria. American Economic Review 88 (4), 848–881.

Gervais, Simon, Odean, Terrance, 2001. Learning to be overconfident. Review of Financial Studies 14 (1), 1–27.

Grinblatt, Mark, Keloharju, Matti, 2001. What makes investors trade? Journal of Finance 56 (2), 589–616.

Hartzmark, Michael L., 1991. Luck versus forecast ability—determinants of trader performance in futures markets. Journal of Business 64 (1), 49–74.

Henriksson, Roy D., Merton, Robert C., 1981. On market timing and investment performance. ii. Statistical procedures for evaluating forecasting skills. Journal of Business 54 (4), 513–533.

Holtz-Eakin, Douglas, Newey, Whitney, Rosen, Harvey S., 1988. Estimating vector autoregressions with panel data. Econometrica 56 (6), 1371–1395.

Investment Company Institute, 2003. Mutual Fund Fact Book.

Jagannathan, Ravi., Korajczyk, Robert A., 1986. Assessing the market timing performance of managed portfolios. Journal of Business 59 (2), 217–235.

Knetsch, Jack L., Sinden, Jack A., 1984. Willingness to pay and compensation demanded: experimental evidence of an unexpected disparity in measures of value. Quarterly Journal of Economics 99 (3).

Kumar, Alok, Lee, Charles M.C., 2006. Retail investor sentiment and return comovements. Journal of Finance 61 (5), 2451–2486.

Linnainmaa, Juhani, 2006. Learning from experience Working paper, pp. 1–35.

List, John A., 2003. Does market experience eliminate market anomalies? Quarterly Journal of Economics 118 (1), 41–71.

Merton, Robert C., 1981. On market timing and investment performance. I. An equilibrium theory of value for market forecasts. Journal of Business 54 (3), 363–406.

Odean, Terrance, 1999. Do investors trade too much? American economic review. American Economic Review 89 (5), 1279–1298.

Sargent, Thomas J., 1993. Rational expectations. The Concise Encyclopedia of Economics. Library of Economics and Liberty ⟨http://www.econlib.org/library/Enc/RationalExpectations.html⟩.

Seru, Amit, Shumway, Taylor, Stoffman, Noah, 2007. Learning by trading Working paper, pp. 1–46.

Shor, Mikhael, 2004. Learning to respond: the use of heuristics in dynamic games Vanderbilt University working paper, pp. 1–23.