Do Individual Investors Learn from Their Trading Experience?*

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Abstract

This paper investigates whether individual investors adjust their stock trading according to their stock selection abilities, which can be inferred from their trading history. Fixed-effect panel regressions provide strong evidence that the ability to forecast future stock returns significantly affects investors' trading activity: investors purchase more actively if they are more likely to have stock selection ability. Furthermore, trading experience – measured by the number of purchases, the number of different stocks purchased, and the variance of purchase dollar amounts – significantly helps improve investors' portfolio performance. In addition, we find that learning behavior varies across investors, which corroborates the heterogeneity of individual investors.

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Rationality of economic agents is a classic assumption in modern economics and finance. This assumption simplifies the decision-making processes associated with constrained optimization problems, so that economic phenomena can be analyzed with mathematical models. An important justification for this assumption is that agents are not likely to make systematic mistakes. For instance, 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). The argument is certainly appealing, but not necessarily substantiated. This paper empirically tests whether a special group of agents - individual investors - learn about their stock selection ability from their own trading experience and adjust their trading behavior accordingly. This study provides direct evidence regarding the fundamental argument of agent rationality: rational investors learn from their mistakes and thus mistakes should not be repeated systematically.

The study of individual learning behavior has important economic implications. First, the growing literature of behavioral economics and finance provides strong evidence that agents are not always fully rational at the aggregate level (see, e.g., Shleifer, 2000; Barberis and Thaler, 2002, for useful surveys). However, there is much less evidence on whether individual economic agents learn to reduce their mistakes over time. Our study helps fill this gap. Second, our study provides empirical evidence regarding the appropriateness of assumed rationality. Specifically, if individuals do not learn, the rationality assumption, as well as the numerous ensuing economic theories, would be challenged. Furthermore, our study is important because it helps facilitate future research concerning the behavior of economic agents by disentangling two possible sources of limited rationality at the aggregate level. One possibility is that individuals are not fully rational and do not learn. Another possibility is that while individuals do learn to become more rational over time, the representative agent remains limitedly rational because amateur agents continually join the economy. In this case, population composition plays a significant economic role.[1]

[1] See Bakshi and Chen (1994) and Ang and Maddaloni (2003) for examples about relations between economy and demography.

We test two hypotheses regarding individual investors' learning behavior. The first hypothesis concerns whether trading history affects future trading activity. We assume individual investors are able to infer their stock selection ability from their trading history. If investors are rational, their inferred stock selection ability should affect their future trading patterns. Specifically, when they think they are able (unable) to select winning stocks, they should trade more (less) actively. The second hypothesis concerns whether trading experience helps improve future portfolio performance. Traders with more experience have more data (i.e., past trading activity) to infer their ability. Therefore, their inferences should be more accurate, which should lead to better trading decisions and hence better portfolio performance.

We use the nonparametric statistical model developed by Henriksson and Merton (1981), modified by Cumby and Modest (1987), and applied by Hartzmark (1991) and others to infer two types of stock selection ability: the ability to forecast the *signs* of future excess stock returns as well as the ability to forecast both the *signs* and *magnitudes* of future excess stock returns. We construct a time-series of inferred ability for each investor, and then use a fixed-effect panel data approach to investigate the effect of the inferred ability on investor trading, controlling for other possible trading-driving variables.

Our empirical results provide evidence that both types of abilities to forecast over the coming month (20 trading days) significantly affect investors' equity purchase decisions, while the ability to make short term (5 trading days) forecasts do not affect purchases. We also find that trading experience helps improve portfolio performance. Particularly, the more experienced an individual investor is (in terms of the number of purchases, the number of stocks purchased, and the variance of purchase dollar amounts), the higher is the future risk-adjusted return of her portfolio. On the other hand, our results also demonstrate behavior variations across different categories of investors. For example, active traders adjust their trading according to their inferred ability more dramatically than inactive traders. Overall, our empirical findings suggest that (i) individual investors rationally learn from their own experience and adjust their stock purchases accordingly, and (ii) learning behavior is heterogeneous across individual investors.

We study individual investors because they are normally considered to be the most uninformed and unskilled economic agents. They seem to be the real-world counterparts to the noise traders described by behavioral models (see, for example, De Long et al., 1990; Shleifer and Vishny, 1997, among others). Individual investors have been modeled or documented to behave in many naïve ways. For example, they may under-react or over-react to news; they may insufficiently or naïvely diversify their portfolios; they may hold too many local or domestic equities; they may make investment decisions based on familiarity instead of utility maximization; and confusion concerning stock tickers may even lead them to respond to news incorrectly.[2] In short, individual investors seem to be making a variety of mistakes that have significant economic consequences. Therefore, they are suitable subjects for investigating potential learning behavior. If they are able to learn rationally, it seems plausible to argue that other more sophisticated economic agents should be able to learn as well.

We study learning behavior pertaining to trading because, unlike other economic processes in which different types of behavior could all be rational, it is easier to identify trading mistakes. Since trading is costly, it is reasonable to argue that individual investors should not trade unless they have legitimate reasons. Legitimate reasons include having (i) *security analysis ability* – the ability to select individual stocks that will outperform the market; (ii) *market timing ability* as defined by Merton (1981) – the ability to forecast stock market performance market relative to fixed-income securities; (iii) a need to rebalance their portfolios due to changes in personal preference or changes in the covariance matrix of asset returns; (iv) a desire to exploit tax benefits; or (v) a need to meet liquidity demands.

Our analysis is based on a sizeable panel data set containing the trading activities of individuals belonging to a large national discount brokerage firm (see Odean 1998 and Barber and Odean 2000 for more descriptions of the data). This data set has several features that dramatically motivate our research. First, the data allow us to observe individuals' detailed trading history (including prices and shares of stock bought and sold on a given date), dramatically facilitating the inference of investor security analysis ability. Second, the data allow us to follow individuals

[2] See for example Alpert and Raiffa (1982), Barber and Odean (2000), Benartzi (2001), Benartzi and Thaler (2001), Coval and Moskowitz (1999), Daniel et al. (1998), Fischoff et al. (1977), Goetzmann and Kumar (2003), Hong and

over a period of six years, which is beneficial because the learning process is naturally a temporal process. Finally, the data set contains a large number of individual investors, therefore we are able to attain more inference power by exploiting the variation across individuals and thus mitigate possible sample selection problems.

It is worth noting that rational learning behavior (i.e., whereby investors adjust their trading according to their inferred ability) relates to but also differs from irrational performance-feedback trading (i.e., whereby investors become overconfident after good performance and consequently trade more actively). First, rational learning captures the relation between *ability* and trading activity, while performance-feedback trading captures the relation between *performance* and trading activity. Good performance does not necessarily suggest skill or ability since performance can be due entirely to luck. Ability is estimated using methodology established in Henriksson and Merton (1981) and modified by Cumby and Modest (1987), which is based on significant statistical relations that are unlikely to be outcomes of chance. Second, performance-feedback trading may suggest asymmetric reinforcement. Good performance may lead to overconfidence and thus more trading, but poor performance does not necessarily lead to less trading. On the other hand, rational learning suggests that investors should adjust their trading activity according to their ability, regardless of their past performance (i.e., good or bad). Finally, rational learning behavior suggests that trading experience should help improve future investor performance, while performance-feedback trading lacks this implication.

This paper relates to literature regarding individual investor trading, which has documented several important, and often not fully rational, behaviors.[3] For example, investors trade excessively: investors who trade the most earn the lowest average returns after transaction costs. Interestingly, on average, men trade more actively yet perform worse than women. Investors who switch from phone-based trading to online trading also trade more and earn lower returns. Additionally, individual investors are often reluctant to realize their losses. Finally, the trading activity of individual investors is affected by past returns and historical price patterns. Our empirical results provide evidence that, despite these irrational behaviors, individual investors

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Stein (1999), Huberman (2001), Ivkovich and Weisbenner (2003), Rashes (2001), Zhu (2003), among others.

rationally learn from their trading experience and adjust their trading according to their stock selection ability, thus indicating the complexity of human behavior.

This paper also relates to recent finding concerning individual investors' ability to beat the market. Coval et al. (2003) show that a portion of individual investors persistently earn average excess returns, suggesting that at least some individual investors are able to select stocks. Our empirical results suggest that individual investors can become better traders over time: if they have (do not have) stock selection ability, they will trade more (less) actively, and trading experience helps them achieve better portfolio performance.

Our empirical evidence corroborates recent findings pertaining to individual learning behavior in marketplaces. Using experiments, List (2003) finds that market experience plays a significant role in eliminating the endowment effect - individual behavior converges to neoclassical predictions as market experience increases. Dhar and Zhu (2003) find that trading experience helps alleviate individual investors' tendency to sell winning stocks too soon and hold losing stocks too long. We find that individual investors, despite their various investment mistakes, are able to achieve better portfolio performance by adjusting their stock purchases according to their trading experience. This finding emphasizes the importance of heterogeneity among economic agents in the economy. The composition of investors, e.g. experienced vs. inexperienced, could potentially influence how the market functions.

The paper proceeds as follows. Section I describes the data. Section II discusses our research design. Section III reports our estimation results. Section IV concludes.

I. Data

The data used in this study come from a large discount brokerage firm, and cover the investments of 78,000 households from January 1991 to December 1996.[4] The data have three important components: (1) Position data record the sample households' end-of-month portfolio

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[3] See Barber and Odean (2000, 2001, 2002a, 2002b), Odean (1998, 1999), and Grinblatt and Keloharju (2001) among others.

[4] The end-of-month portfolio position data is available from January 1991 to January 1997. The trade data is available from January 1991 to November 1996.

positions. (2) Trade data record all trades made by sample investors. Both the trading and position files include common stocks, mutual funds, and other securities (i.e., American Deposit Receipt, fixed income securities, and options). (3) An investor characteristics file includes investor characteristics such as investors' income levels, occupation categories, ages, and when they opened their accounts.

In this study, we focus on investors' stock selection ability so we exclude 11,535 investors who do not hold common stocks in any month of our sample period. Sample households can open multiple accounts at the discount brokerage firm. An average sample household has two accounts. The most common reason for two accounts is the tax-preferred status of retirement accounts. Common stocks make up roughly 60 percent of the account values and slightly more than 60 percent of all trades.

The dataset is filtered as follows: First, if a household has multiple trading accounts, we treat these accounts as one large account, aggregating monthly trades across all accounts associated with a particular household. Then, only households that opened their first account in 1990 or 1991 are examined because their entire timeline of trading activity beginning with their very first trade can be observed. 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 sample of 65,118 household-months for 2,973 households, spanning the calendar time March, 1991 to November, 1996.

Table 1 summarizes the trading activities and shows that individual investors have very different trading behavior. For example, the average number of trades per month varies dramatically from a minimum of 0 to a maximum of 113.0; the average number of buys per month varies from 0 to 49.67; and the average number of sells varies from 0 to 63.33.

II. Research Design

We test two null hypotheses regarding investors' learning behavior: (i) investors' stock purchases are not affected by their security analysis ability, which they estimate using past purchases and post-purchase stock returns; (ii) trading experience does not help investors improve the performance of their portfolios. To test the first hypothesis, we construct monthly series of security analysis ability proxies for each investor, then run fixed effect regressions of the number of stock purchases on the ability proxies, controlling for other variables that may affect stock purchases. Two types of security analysis abilities are studied: the ability to forecast the *signs* of future risk-adjusted excess stock returns and the ability to forecast both the *signs* and the *magnitudes* of future risk-adjusted excess stock returns, where the *future* is defined as the 5 and 20 trading days following the purchase, respectively. To test the second hypothesis, we construct time series of 3 different measures of trading experience for each household, and run fixed effect regressions of investors' portfolio risk-adjusted excess return on the trading experience measures.

We follow Coval et al. (2003) and use trades that initiate or expand existing positions in companies in order to infer investors' abilities. Essentially, we consider buys as predictions of future price increases, but do not consider sales as predictions of future price decreases. The rationale is, as Coval et al. (2003) argue, that sales are often not strongly driven by private information or specific analysis of the sold stock. Instead, investors may sell to satisfy liquidity needs or to move into other firms expected to outperform the market, etc. We also ignore short-sales since there are very few occurrences.

Does Ability Affect Future Purchases?

The evaluation of investors' forecasting ability is a well-studied problem in finance (see Becker et al., 1999, Henriksson and Merton, 1981, Cumby and Modest, 1987, Hartzmark, 1987 and 1991, Jagannathan and Korajczyk, 1986, and Merton, 1981, among many others). It is conventional (e.g., Merton, 1981) to partition forecasting skills into "microforecasting" and "macroforecasting," defined as forecasting individual stocks' price movements relative to the market and stock market price movements relative to fixed-income securities, respectively. The former is frequently referred to "security analysis" and the latter is termed "market timing." This paper focuses on investors' security analysis abilities.

The first type of security analysis ability we study is the ability to forecast the signs of future risk-adjusted excess stock returns. A classic approach to evaluate this type of ability is developed by Henriksson and Merton (1981) and later modified by Cumby and Modest (1987) and concerns whether the conditional probability of correctly forecasting the signs of future price changes significantly differs from 0.5. This approach and its extensions are widely used to study the performance of mutual funds and futures market traders, as well as the forecasting ability of newsletters.[5] Since we study only purchases, inferring security analysis ability is dramatically simplified under the assumption that investors are equally capable of forecasting future price increases and decreases.

The inference of investors' abilities to forecast the *signs* of future risk-adjusted excess returns consists of the following steps. First, we estimate the risk-adjusted excess return of purchased stocks in the week (5 trading days) and month (20 trading days) after the purchases, respectively. The different horizons are chosen to investigate investors' ability to forecast short-term and longer-term excess returns. To do this, for each purchased stock, we first run a time series regression of its daily returns net the Treasury-bill rates on the Fama-French factors using a time window spanning 100 trading days before to 100 days after the purchase day. The stock's excess return over the week or month following the purchase is the sum of its estimated regression intercept and the error terms during the period in question; or equivalently, the realized return minus the sum of the estimated factor loadings times the realized value of each of the factors. We start with the day following the purchase to mitigate possible price impacts.

For investor i at the beginning of month t, the information with which the investor can infer her ability includes $N_{i,t}$ and $G_{i,t}$. $N_{i,t}$ is the number of purchases made at least 5 or 20 trading days before t (depending on the forecasting time horizon). $G_{i,t}$ is the number of *good* purchases, which are purchases with nonnegative risk-adjusted excess returns over the 5 or 20 subsequent trading days (depending on the forecasting time horizon). Assuming the sign of the excess return is generated from a binomial process, the null hypothesis is that the probability that the risk-adjusted excess return conditional upon purchase will be positive is 0.5. A two-sided test of the hypothesis is straightforward, and we follow Hartzmark (1991) and define a proxy for the security selection ability as

[5] See Bollen and Busse (2001), Chance and Hemler (2001), Graham and Harvey (1996), and Womack (1996), among others.

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

This proxy incorporates information on the direction and significance of the ability. For example, if $G_{i,t}/N_{i,t}$ equals 0.8 and the probability significance level is 0.15, then $FS_{i,t} = (1-0.15)\times 1 = 0.85$. Therefore, the range $(-1 \le FS_{i,t} \le 1)$ encompasses the universe of investors: those with statistically significant inferior ability, those with no ability, and those with statistically significant superior ability. To differentiate the ability estimated using the risk-adjusted excess return in the week after the purchase from that estimated using the excess return over the following month, we denote the former by $FS_{i,t}^{5}$ and the latter by $FS_{i,t}^{20}$.

Hartzmark (1991) defines the big hit ability as the capability to predict both the *magnitude* and *direction* of future price changes. Investors with superior big hit ability will establish larger long positions when higher excess returns are anticipated. At time t, denote by $R_{i,j}$ the subsequent risk-adjusted excess return of the j^{th} stock purchased by investor i, and by $D_{i,j}$ the dollar amount of the purchase (the number of shares multiplied by the transaction price). At the beginning of month t, we run a times-series regression investor i,

$$R_{i,j} = \alpha + \beta_{i,t} D_{i,j} + \varepsilon_{i,j}, \quad (2)$$

using all purchases made 5 or 20 trading days before t, respectively. To incorporate information on the sign of the estimator of β, standard errors, and degree of freedom into one aggregate measure, we follow Hartzmark (1991) and define the big hit ability for investor i at t, $FB_{i,t}$, as

$$FB_{i,t} = \left(1 - \text{probability significance level}_{i,t}\right) \times \left(\text{sign of } \beta_{i,t}\right). \quad (3)$$

Apparently, the range of $FB_{i,t}$ is still $(-1,1)$. To differentiate $FB_{i,t}$ estimated using the excess return in the week after the purchase from that estimated using the excess return in the following month, we denote the former by $FB_{i,t}^{5}$ and the latter by $FB_{i,t}^{20}$.

We study the relation between investors' purchases and security analysis abilities using the following fixed effect regression.

$$T_{i,t} = c_i + \rho_1 F_{i,t} + \rho_2 T_{i,t-1} + \rho_3 R_{m,t-1} + \rho_4 R_{i,t-1} + \rho_5 P_{i,t-1} + \rho_6 \left(SD_{m,t} - SD_{m,t-1} \right) + \rho_7 GR3_{m,t-1} + \rho_8 V_{m,t-1} + \rho_9 DEC_t + \rho_{10} JAN_t + \varepsilon_{i,t} \qquad (4)$$

In equation (4), $T_{i,t}$ is the number of purchases made by investor i in month t; $F_{i,t}$ is investor i's security analysis ability and takes the value of $FS_{i,t}^5$, $FS_{i,t}^{20}$, $FB_{i,t}^5$ and $FB_{i,t}^{20}$, respectively; $R_{m,t-1}$ is the lagged S&P500 index return; $R_{i,t-1}$ is the lagged personal portfolio return of the investor; $P_{i,t-1}$ is the market value of investor i's portfolio (consisting of both mutual funds and stocks) at the end of month $t-1$; $SD_{m,t}$ is the cross-sectional standard deviation of all stock returns in the market, and $SD_{m,t} - SD_{m,t-1}$ captures the change in the cross-stock return standard deviation; $GR3_{m,t-1}$ is the compounded return of S&P500 over the past three years; $V_{m,t-1}$ is the dollar value of NYSE/AMEX/NASDAQ stocks traded in the prior month; DEC_t is a dummy variable for December; and JAN_t is a dummy variable for January.

Equation (4) includes $F_{i,t}$ as an explanatory variable to study whether security analysis ability affects trading. If an investor is rational, when $F_{i,t}$ is positive, she should capitalize on her ability by purchasing stocks more actively, and when $F_{i,t}$ is negative, she should reduces her trading activity. Therefore, a positive ρ_1 is consistent with the existence of rational investor learning.

Besides $F_{i,t}$, we include other explanatory variables in equation (4) to control for other trading needs. First, we include lagged purchases to control for possible serial correlation in trading activity. Second, we use the change in cross-sectional standard deviation of all stocks returns in the market as a proxy for the change in the covariance of stock returns to control for rational portfolio rebalancing. In addition, we include lagged market and personal portfolio returns. The lagged personal portfolio return helps control for performance-feedback trading, and the lagged long-run historical market performance helps capture the possible evolution of trading behavior, such as that caused by changing investor sentiment correlated with market trends. In addition, we include the lagged market value of investors' portfolios to control for possible relations between trading and portfolio size. For instance, some investors may cease trading simply because they have consumed almost all of their wealth and thus have no money with which to trade. We also include lagged market trading volume in dollar terms to control for fads and/or herding in the investment market. Furthermore, we use December and January dummy variables to capture possible trading seasonality (see e.g., Kumar and Lee, 2002). Finally, we include an individual time-invariant intercept to capture trading associated with time-invariant components of latent variables such as the investor's risk attitude, gender, personal income, education, etc. Other trading needs are captured by the error term.

Does Experience Help Improve Performance?

If investors rationally learn from past trading, as an investor's trading experiences increases (e.g., more purchase transactions and/or more stocks purchased) so does the information set with which the investor estimates her stock selection ability. This larger sample size should improve the precision of the ability estimates, and subsequent trading decisions should improve performance more significantly.

We first construct monthly time series of risk-adjusted portfolio returns, $RER_{i,t}$, for each investor by adding the estimated intercept term to the estimation residuals of the regression of monthly investor portfolio returns net the Treasury-bill rates on the Fama-French factors. These risk-adjusted portfolio returns are measures of investors' portfolio performance. We use three measures of the trading experience, denoted by $E_{i,t}$. The first measure is simply the number of all purchases made before t: $\sum_{s=1}^{t-1} T_{i,s}$. The second measure is the number of different stocks an investor has ever purchased prior to time t. The third measure is the variance of the dollar amounts of purchases prior to t. It is not implausible to argue that the more purchases an investor has made and the more different stocks an investor has purchased, the better equipped she is to infer her security analysis ability. Furthermore, the larger is the variance of the explanatory variable, which is the dollar amounts of purchases in regression (2), the more accurately the big hit ability can be estimated.

We investigate the relation between trading experience and portfolio performance using the following fixed effect regression.

$$RER_{i,t} = c_i + \rho E_{i,t} + \varepsilon_{i,t} \quad (5)$$

In (5), $RER_{i,t}$ is the estimated risk-adjusted excess return of investor i's portfolio at time t; $E_{i,t}$ is investor i's trading experience at time t, and can assume three measures respectively; c_i is an individual time-invariant intercept that captures unobserved individual specific factors; $\varepsilon_{i,t}$ is a zero mean error term. A positive ρ is consistent with the existence of rational investor learning.

Sub-sample Analysis

We conduct a variety of sub-sample studies. First, we re-estimate equations (4) and (5) using data in odd and even transaction months. Second, we re-estimate the equations for two categories of investors: active traders (complete at least 25 trades in the sample period) and inactive traders. Finally, we re-estimate the equations after categorizing investors according to their average excess portfolio performance as winners (top one third), average (middle one third), and losers (bottom one third).

The results of these sub-sample studies may have different interpretations. Under the assumption of homogenous investors, these studies are robustness checks. However, allowing for the heterogeneity of investors, these studies may reveal systematic differences between different types of individual investors.

III. Empirical Results

Table 2 reports the results of regression (4) based on all investors in our sample. First, we find that the coefficients of both $FS_{i,t}^{20}$ and $FB_{i,t}^{20}$ are significantly positive at the 1% level. Therefore, we reject the null hypothesis that investors' stock purchases are not affected by their abilities to forecast the signs and magnitudes of excess stock returns over the time horizon of 20 business days. Furthermore, the positive signs of the coefficients are consistent with the rational learning hypothesis: when investors believe they are able to forecast excess returns, they purchase more actively; when they do not believe in their ability, they reduce their stock purchases. Note that the past performance of investors and the stock market have been controlled, so our results are not caused by performance-feedback trading. At the same time, we find that $FS_{i,t}^{5}$ significantly reduces stock purchases and $FB^{5}_{i,t}$ is insignificant, which suggests that investors do not adjust their purchases according to their ability to forecast excess returns over the time horizon of 5 business days. Consequently, we can not reject the null hypothesis that investors are not learning from their trading experience. However, it is worth noting that the negative or insignificant coefficients do not necessarily *support* the null hypothesis. There are a variety of possible reasons why rational learning investors may not adjust their stock purchases according to their ability to forecast short term excess returns. For example, individual investors may simply intend to profit in a longer time horizon.

Tables 3 to 9 report the results of regression (4) using different sub-samples. Tables 3 and 4 report the results based on observations in each investor's odd and even transaction months. Tables 5 and 6 examine active and inactive investors. Tables 7, 8, and 9 are for households whose arithmetic average monthly portfolio return in excess of the market return belonged in the top, middle, and bottom one third of the distribution. These tables suggest that, on one hand, the learning behavior we find in table 2 is observed in most sub sample studies. First, the coefficient of $FS^{20}_{i,t}$ is significantly positive except for winners and even transaction months, for which the coefficient is insignificant. It is worth noting that an insignificant coefficient does not necessarily suggest that investors do not learn. It is possible that the insignificant coefficient of winners is an artifact. For example, the number of purchases made by winners may be relatively stable even if they actively learn and trade accordingly, because investors' purchasing activity can be limited by their wealth levels. Second, the coefficient of $FB^{20}_{i,t}$ is significantly positive except for inactive traders, average performance and losers, for which the coefficient is insignificant. On the other hand, tables 3 to 9 also suggest the learning behavior differs across investors. For instance, losers respond more dramatically to their ability to forecast the direction of future excess returns, while winners do not seem to respond. However, the differences may not be surprising since the heterogeneity of economic agents is an expected and established fact.

Table 10 reports the results of regression (5) using the full sample along with different sub-samples. All three proxies are significantly positive, which rejects the null hypothesis that trading experience does not help improve portfolio performance and is consistent with rational investor learning behavior. The sub-sample studies, on the other hand, suggest heterogeneity across investors. For example, inactive traders benefit much more significantly from the number of prior purchases and the number of different purchased stocks than active traders. In addition, investors with average performance benefit more from their trading experience than winners and losers.

IV. Conclusions

This paper investigates whether a special group of economic agents - individual investors - learn about their stock selection ability from their own trading experience and then accordingly adjust their stock trading activity. We find that stock selection ability – particularly the ability to forecast the signs and both the signs and magnitudes of excess stock returns in coming month – significantly affects stock purchases. However, the ability to make short term (5 trading days) forecasts does not affect purchasing activity. We also find that trading experience helps improve portfolio performance. Particularly, as an investor completes more purchase transactions and purchases more unique stocks, her portfolio's subsequent risk-adjusted monthly return is higher. Overall, our empirical findings are consistent with the hypothesis that individual investors (despite making numerous documented mistakes) learn from their own trading experience, adjust their stock purchases accordingly, and achieve higher portfolio performance. Our empirical results also highlight the importance of individual investor heterogeneity. Specifically, learning behavior varies across different categories of investors. For example, active traders adjust their stock purchases according to their abilities more dramatically than inactive traders.

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Table 1
Data Summary: Trading Activities

This table reports summary statistics of the trading activities of households who opened their first accounts in 1990 and 1991, respectively.

Average number of trades per month					
Accounts	Min	25%	Median	75%	Max
1990	0.00	0.17	0.38	0.80	43.16
1991	0.00	0.15	0.34	0.79	113.00
Total	0.00	0.16	0.37	0.79	113.00
Average number of buys per month					
Accounts	Min	25%	Median	75%	Max
1990	0.00	0.09	0.21	0.45	21.06
1991	0.00	0.07	0.19	0.45	49.67
Total	0.00	0.08	0.20	0.45	49.67
Average number of sells per month					
Accounts	Min	25%	Median	75%	Max
1990	0.00	0.07	0.17	0.37	22.09
1991	0.00	0.05	0.14	0.36	63.33
Total	0.00	0.06	0.15	0.36	63.33

Table 2
Security Analysis Ability and Stock Purchases

This table reports the results of the following fixed effect regression.

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

$T_{i,t}$ is the number of purchases household i made in month t. $F_{i,t}$ takes on the value of $FS^5_{i,t}$, $FS^{20}_{i,t}$, $FB^5_{i,t}$ and $FB^{20}_{i,t}$, respectively. $FS^5_{i,t}$ and $FS^{20}_{i,t}$ measure investors' abilities to forecast the signs of future excess returns in the coming week (5 trading days) and month (20 trading days), respectively. $FB^5_{i,t}$ and $FB^{20}_{i,t}$ measure investors' abilities to forecast both the signs and magnitudes of future excess returns in the coming week and month, respectively. Additional explanatory variables are lagged purchases $T_{i,t-1}$, 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 are multiplied by 1,000,000), change of cross-sectional standard deviation of stock returns in the market $SD_{m,t} - SD_{m,t-1}$, lagged three-year S&P500 return $GR3_{m,t-1}$, dollar value of NYSE/AMEX/NASDAQ stocks traded in the prior month $V_{m,t-1}$, and December DEC_t and January JAN_t dummy variables. Coefficients with * are significant at the 5% level, and coefficients with ** are significant at the 1% level.

	$FS^5_{i,t}$	$FS^{20}_{i,t}$	$FB^5_{i,t}$	$FB^{20}_{i,t}$
ρ_1	*-0.044	**0.073	0.009	**0.054
ρ_2	**0.262	**0.262	**0.262	**0.262
ρ_3	**0.811	**0.805	**0.811	**0.812
ρ_4	**0.148	**0.147	**0.148	**0.147
ρ_5	**-0.375	**-0.385	**-0.380	**-0.383
ρ_6	**0.421	**0.424	**0.422	**0.421
ρ_7	**0.511	**0.504	**0.509	**0.509
ρ_8	**-0.000	**-0.000	**-0.000	**-0.000
ρ_9	-0.027	-0.027	-0.027	-0.027
ρ_{10}	*0.045	*0.045	*0.045	*0.045

Table 3
Security Analysis Ability and Stock Purchases: Odd Months

This table reproduces Table 2 but only uses data for each household's odd moths (transaction time). Coefficients with * are significant at the 5% level, and coefficients with ** are significant at the 1% level.

	$FS_{i,t}^{5}$	$FS_{i,t}^{20}$	$FB_{i,t}^{5}$	$FB_{i,t}^{20}$
ρ_1	-0.016	**0.108	-0.029	*0.057
ρ_2	**0.291	**0.290	**0.291	**0.290
ρ_3	**0.955	**0.941	**0.955	**0.955
ρ_4	*0.127	*0.127	*0.127	*0.126
ρ_5	-0.077	-0.085	-0.077	-0.084
ρ_6	**0.467	**0.469	**0.465	**0.467
ρ_7	**0.528	**0.521	**0.529	**0.527
ρ_8	**-0.000	**-0.000	**-0.000	**-0.000
ρ_9	-0.015	-0.014	-0.015	-0.015
ρ_{10}	0.050	0.050	0.050	0.050

Table 4
Security Analysis Ability and Purchases: Even Months

This table reproduces Table 2 but only uses data for each household's even months (transaction time). Coefficients with * are significant at the 5% level, and coefficients with ** are significant at the 1% level.

	$FS_{i,t}^{5}$	$FS_{i,t}^{20}$	$FB_{i,t}^{5}$	$FB_{i,t}^{20}$
ρ_1	*-0.071	0.041	0.045	*0.051
ρ_2	**0.231	**0.231	**0.231	**0.231
ρ_3	*0.664	*0.660	*0.661	*0.663
ρ_4	**0.167	**0.167	**0.167	**0.167
ρ_5	**-0.681	**-0.693	**-0.688	**-0.692
ρ_6	*0.379	*0.385	*0.382	*0.383
ρ_7	**0.496	**0.491	**0.492	**0.494
ρ_8	**-0.000	*-0.000	*-0.000	*-0.000
ρ_9	-0.041	-0.041	-0.041	-0.041
ρ_{10}	0.041	0.042	0.042	0.042

Table 5
Security Analysis Ability and Purchases: Active Traders

This table reproduces Table 2 but only uses households that performed at least 25 transactions throughout the entire sample period. Coefficients with * are significant at the 5% level, and coefficients with ** are significant at the 1% level.

	$FS_{i,t}^{5}$	$FS_{i,t}^{20}$	$FB_{i,t}^{5}$	$FB_{i,t}^{20}$
ρ_1	*-0.084	**0.084	0.018	**0.075
ρ_2	**0.280	**0.280	**0.280	**0.280
ρ_3	**1.408	**1.391	**1.406	**1.409
ρ_4	**0.207	**0.206	**0.207	**0.206
ρ_5	*-0.414	*-0.429	*-0.422	*-0.426
ρ_6	**0.650	**0.652	**0.651	**0.650
ρ_7	**0.721	**0.716	**0.723	**0.721
ρ_8	-0.000	-0.000	-0.000	-0.000
ρ_9	-0.026	-0.026	-0.026	-0.026
ρ_{10}	0.070	0.070	0.070	0.071

Table 6
Security Analysis Ability and Purchases: Inactive Traders

This table reproduces Table 2 but only uses households who performed less than 25 transactions throughout the entire sample period. Coefficients with * are significant at the 5% level, and coefficients with ** are significant at the 1% level.

	$FS_{i,t}^{5}$	$FS_{i,t}^{20}$	$FB_{i,t}^{5}$	$FB_{i,t}^{20}$
ρ_1	**0.051	**0.064	0.006	0.012
ρ_2	0.007	0.007	0.008	0.008
ρ_3	-0.022	-0.023	-0.024	-0.024
ρ_4	0.033	0.033	0.033	0.033
ρ_5	**-0.331	**-0.334	**-0.327	**-0.328
ρ_6	0.025	0.026	0.024	0.024
ρ_7	**0.339	**0.340	**0.343	**0.343
ρ_8	**-0.000	**-0.000	**-0.000	**-0.000
ρ_9	**-0.031	**-0.031	**-0.031	**-0.031
ρ_{10}	0.009	0.009	0.008	0.008

Table 7
Security Analysis Ability and Purchases: Winners

This table reproduces Table 2 but only uses households whose arithmetic average monthly portfolio return in excess of the market return belonged in the top one third of the sample. Coefficients with * are significant at the 5% level, and coefficients with ** are significant at the 1% level.

	$FS_{i,t}^{5}$	$FS_{i,t}^{20}$	$FB_{i,t}^{5}$	$FB_{i,t}^{20}$
ρ_1	*-0.114	-0.009	0.026	**0.154
ρ_2	**0.329	**0.329	**0.329	**0.328
ρ_3	**1.292	**1.287	**1.285	**1.278
ρ_4	**0.145	**0.145	**0.145	**0.144
ρ_5	-0.287	-0.299	-0.294	-0.294
ρ_6	*0.471	*0.473	*0.474	*0.471
ρ_7	**0.461	**0.464	**0.464	**0.459
ρ_8	0.000	0.000	0.000	0.000
ρ_9	-0.046	-0.046	-0.046	-0.046
ρ_{10}	0.067	0.067	0.067	0.067

Table 8

Security Analysis Ability and Purchases – Performance Groups (Average)

This table reproduces Table 2 but only uses households whose arithmetic average monthly portfolio return in excess of the market return belonged in the middle one third of the sample. Coefficients with * are significant at the 5% level, and coefficients with ** are significant at the 1% level.

	$FS_{i,t}^{5}$	$FS_{i,t}^{20}$	$FB_{i,t}^{5}$	$FB_{i,t}^{20}$
ρ_1	**-0.116	**0.080	0.045	-0.031
ρ_2	**0.177	**0.177	**0.177	**0.177
ρ_3	0.514	0.507	0.516	0.515
ρ_4	**0.286	**0.287	**0.287	**0.288
ρ_5	0.046	0.006	0.026	0.032
ρ_6	**0.404	**0.407	**0.406	**0.406
ρ_7	**0.516	**0.509	**0.513	**0.515
ρ_8	**-0.000	**-0.000	**-0.000	**-0.000
ρ_9	0.003	0.003	0.003	0.003
ρ_{10}	0.046	0.045	0.045	0.045

Table 9
Security Analysis Ability and Purchases – Performance Groups (Losers)

This table reproduces Table 2 but only uses households whose arithmetic average monthly portfolio return in excess of the market return belonged in the bottom one third of the sample. Coefficients with * are significant at the 5% level, and coefficients with ** are significant at the 1% level.

	$FS_{i,t}^{5}$	$FS_{i,t}^{20}$	$FB_{i,t}^{5}$	$FB_{i,t}^{20}$
ρ_1	**0.180	**0.184	*-0.077	0.032
ρ_2	**0.247	**0.246	**0.248	**0.248
ρ_3	0.485	0.477	0.477	0.481
ρ_4	0.060	0.062	0.063	0.064
ρ_5	**-0.915	**-0.915	**-0.902	**-0.904
ρ_6	*0.356	*0.365	*0.358	*0.355
ρ_7	**0.577	**0.578	**0.601	**0.592
ρ_8	**-0.000	**-0.000	**-0.000	**-0.000
ρ_9	*-0.060	*-0.060	*-0.061	*-0.060
ρ_{10}	0.024	0.024	0.023	0.023

Table 10
Trading Experience and Portfolio Performance

This table reports the results of fixed effect regressions that test whether investors' experience helps increase the risk adjusted excess returns of their portfolios.

$$RER_{i,t} = c_i + \rho E_{i,t} + \varepsilon_{i,t}$$

$RER_{i,t}$ is the Fama French three factor-adjusted excess portfolio return of household i at month t, and $E_{i,t}$ is household i's trading experience prior to t, which is measured by three different proxies. The first experience proxy is household i's number of purchase transactions. The second proxy is the number of different stocks household i has ever purchased. The third proxy is the variance of the dollar amounts of household i's purchases. Coefficients have been multiplied by 1,000,000. Coefficients with * are significant at the 5% level, and coefficients with ** are significant at the 1% level.

	Proxy 1	Proxy 2	Proxy 3
All samples			
Coefficient	**131.255	**366.745	**0.000
Odd Months			
Coefficient	100.198	*340.954	0.000
Even Months			
Coefficient	**163.004	**391.744	*0.000
Active Traders			
Coefficient	**116.248	**322.120	*0.000
Inactive Traders			
Coefficient	**2280.551	**2659.029	0.000
Winners			
Coefficient	115.402	316.317	0.000
Average			
Coefficient	**213.002	**396.693	0.000
Losers			
Coefficient	89.677	433.041	0.000