Households Learning in the Dark: Evidence from Retail Traders

Jean-Noël Barrot*

August 27, 2012

Abstract

This paper develops the idea that households have an imprecise knowledge of their portfolio's exposure to systematic risk and that this leads them to make investment mistakes. This idea is tested in the context of the decision to actively trade rather than passively invest in the stock market. I show that the trading activity of individual investors increases (decreases) following high (low) performance. I carefully split individual investors performance into (i) the component of their performance related to the exposure of their trades to systematic risk factors and (ii) residual performance and show that their trading activity reacts to both. To account for these results, I contrast a story based on overconfidence against a simple model where individual investors have an imprecise knowledge of *both* their ability and systematic exposure ex ante, and learn about them as they trade. This model generates predictions consistent with the above evidence as well as additional predictions that are also borne out by the data.

Keywords: Learning, individual investor behavior, individual investor performance, household finance

JEL classification: D10, G11

*PRELIMINARY AND VERY INCOMPLETE. COMMENTS WELCOME. HEC Paris, Economics and Finance Department, 1, rue de la Libération, 78350, Jouy-en-Josas, France. Contact: jean-noel.barrot@mailhec.net. I am greatly indebted to participants to the HEC Finance Brownbag and the MIT Finance Lunch and in particular to David Thesmar, Thierry Foucault, François Derrien, Jérôme Dugast, Luc Goupil and Philippe Rolet. I also received very helpful comments from Robin Greenwood, Daniel Dorn and Terrence Henderschott. I thank EUROFIDAI for providing exhaustive and reliable market data on French stocks. I acknowledge the support from the AXA Research Fund and the HEC Paris Foundation. All remaining errors are mine.

1 Introduction

Investing optimally is a challenge which households seem to handle unequally. Recent studies have shown that they invest sub-optimally due to a number of behavioral biases (Stango and Zinman, 2009) or lack of financial literacy (Van Rooij et al., 2007; Lusardi and Mitchell, 2008; Lusardi and Tufano, 2009). Other contributions to this literature argue that at least some households display a high level of rationality and sophistication (Calvet et al., 2006, 2009a,b). The reasons why some households do not seem to manage their financial wealth optimally is an important question with significant welfare implications. This paper shows that some investment mistakes that we observe in the data might result from the imprecise knowledge that households have of the exposure of their portfolio to systematic risk.

I consider the decision to actively trade, rather than passively invest in the stock market. I use a 10 year long, unique and large sample of French retail traders provided by a leading European broker in personal investing and online trading. To identify the decision to actively trade, I use the "Differed Settlement Service" (henceforth "SRD") a specific feature of the French stock exchange (Euronext), launched in September 2000 and aimed at individual investors. This service enables them to initiate long or short positions on a list of eligible securities only putting a portion of the value of the position forward. The SRD is a service that brokers may or may not offer to their clients and which comes with related fees. The online broker which provided the data used in this paper has been offering this service since it was launched. Since individual investors posting trades on the SRD have to pay a fee to use the service, I am confident that only investors who are willing to actively trade will self select into this service.

Consistent with the literature, I observe that individual investors increase their active trading activity following good performance. More interestingly, I carefully split individual investors performance into (i) performance related to the exposure of their trades to systematic risk factors such as the market premium, the excess returns on small stocks and the excess returns on value stocks (henceforth "factor exposure performance") and (ii) residual performance (henceforth "alpha") and show that trading activity reacts to both (i) and (ii). I ask whether this can be explained by market timing or by the ability of individual investors to predict the returns of systematic risk factors and to modify their exposure to those risk factors accordingly. Instead I find that the exposure of individual investors trades to systematic risk factors (henceforth "beta") remains remarkably stable.

These results suggest that some individual investors are actively trading although they would be better off by passively investing. Understanding why this happens is important. It could be that households suffer from a bias of overconfidence and overestimate the signal that past performance sends them about their own ability. This paper develops and tests an alternative story in which these patterns are due to individual investors' imprecise knowledge of their portfolio exposure to systematic risk. I present a simplified three period learning model in which individual investors allocate their wealth between active trading and passive investment in the stock market. When they passively invest in the stock market, they obtain the market return times their beta, i.e. their exposure to market returns, which I assume constant through time. When they actively trade, they obtain alpha, which I assume constant through time, in addition to the market return times their beta. Initially, they do not know alpha and beta. At the end of each period, they observe the market return and their own return and have to decide whether they should actively trade or passively invest in the next period. Ultimately, in the last period, once uncertainty is resolved, they actively trade only if they have a positive alpha. Before then, they have to trade to learn about their alpha. This model generates predictions consistent with the evidence highlighted in the data: active trading is sensitive to both alpha and beta related performance. Moreover, the model generates additional predictions regarding learning dynamics: (i) active trading sensitivity to past performance is smaller when factor returns have been large in absolute value, (ii) the sensitivity of active trading to alpha and factor exposure performance respectively increases and decreases as individual investors learn, and (iii) individuals with high factor exposure performance early in their active investment career stay active longer than individuals with low factor exposure performance early in their active investment career, independently of their respective alpha. I provide evidence supporting these three additional predictions in the sample.

Some individuals investors lose money by actively trading for too long despite a negative alpha or by quitting too early despite a positive alpha. Hence, understanding how they take their trading decision is important: if they trade to learn, then tools properly designed to help households figure out their risk exposure would probably save them time and money.

The learning model presented in the paper is close to those used by Mahani and Bernhardt (2007) and Linnainmaa (2011) who show that individuals find it optimal to trade even if they expect to lose money, as long as the expected short-term loss from trading is offset by the expected gain from learning. These papers motivate the fact that people have to trade to learn about their ability rather than run simulations before they start to trade ("paper learn") as follows. First, a major technical issue with active trading simulation is the difficulty to precisely estimate the actual price at which any given asset would actually be bought or when a limit order would actually be executed since order book data is hard to collect in real time. Second, investing real money is a strong commitment device to provide the best efforts while "paper learning" may lack one.

The addition of this paper to the frameworks developed in these two papers is the assumptions that individual investors performance depends on the exposure of their trades to factor returns and that they initially don't know their exposure to factor returns, i.e. their beta. The assumption that individual investors have imprecise knowledge of their portfolio beta and have to learn about it is consistent with survey evidence on individual investors Glaser and Weber (2007a, 2009). It is also the assumption is a number of finance models. In Chevalier and Ellison (1997, 1999), for instance, mutual fund investors are shown to react to market adjusted performance and less so to beta-adjusted performance. This suggests that individual investors use 1 as a benchmark for the beta of their investments. Individual investors could ignore their true beta when they start trading either because they are financially illiterate or because it would be more costly for them to invest in the technology to compute beta than to trade for a while and incur the loss associated with negative alpha. Unfortunately, I'm unable to differentiate these two explanations in my data. Finally, recent findings in this field show that individual investors have preferred trading habitat, which means that they trade a limited number of assets with similar characteristics (Dorn and Huberman, 2010; Kumar et al., 2011).

This paper contributes to several strands of the literature. It first adds to the recent academic interest for the role of investors' experience and learning process on financial outcome. The fact that investors' own experience shape their future decisions has been shown in the context of IPOs (Kaustia et al., 2008; Chiang et al., 2011), retirement savings decisions (Choi et al., 2009) and mutual funds management (Greenwood and Nagel, 2009) with potential asset pricing implications. More generally, (Malmendier and Nagel, 2011) argue that individuals' experience of macro-economic outcome have long-term effects on their risk taking, which has an impact on aggregate stock price dynamics.

Learning may occur in a variety of ways. Investors may gradually discover the true value of model parameters by rationally updating their priors in a Bayesian way after each action (Pastor and Veronesi, 2009). Investors may as well update their beliefs in a non-Bayesian way as in Gervais and Odean (2001). Learning by doing is another way to model the evolution of investors' behavior (Nicolosi et al., 2009; Seru et al., 2009). This kind of learning is not the focus of this paper. Seru et al. (2009) show that individual investors behavior is consistent with both learning about one's ability and learning by doing but that the former is much more quantitatively significant than the later. Finally, List (2003), Agarwal et al. (2008) and Kaustia et al. (2008) show in various frameworks that with experience, investment behaviors tend to get closer to what full rationality would command.

This paper also adds to the literature on retail traders' behavior. A number of stylized facts have been established by this literature. On average, the average household trades in excess of what liquidity and hedging motives would command and loses money in the process (Barber and Odean, 2000; Barber et al., 2006; Grinblatt and Keloharju, 2000) especially when going online (Barber and Odean, 2002). This is generally attributed to behavioral biases such as overconfidence or gambling (Statman et al., 2006; Glaser and Weber, 2007b; Grinblatt and Keloharju, 2009; French, 2008). Some retail traders however manage to generate absolute performance (Barber et al., 2006; Grinblatt et al., 2009), with some persistence (Coval et al., 2005). Individual investors usually react to past performance by increasing their subsequent trading activity (Glaser and Weber, 2009; Nicolosi et al., 2009). Finally, individual investors have preferred trading habitat, which means that they trade a limited number of assets with similar characteristics (Dorn and Huberman, 2010; Kumar et al., 2011).

The idea developed and tested in this paper is likely to apply to various alternative contexts. It could apply, for instance, to the behavior of retail mutual fund investors.

The rest of this paper is organized as follows. Section 2 develops the simple trading model. In section 3, I define the measures of performance and trading activity used in the empirical analysis. Section 4 presents the data and section 5 describes the results. Predictions regarding learning dynamics are tested in section 6. Section 7 concludes.

2 A simple trading model

In this section I present a simplified three period learning model which predicts that active trading is sensitive to past performance. More specifically, it predicts that active trading is sensitive to *both* performance related to the exposure to systematic risk *and* residual performance. Moreover, it delivers additional predictions which distinguishes it from a story based on overconfidence.

Individual investors allocate their wealth between active trading and passive investment in the stock market with only one risk factor, the market factor. When individual investors passively invest in the stock market returns, they obtain the market return times their beta, i.e. their exposure to the market, which I assume constant through time. When they actively trade, they obtain alpha, which I assume constant through time, in addition to the their market exposure performance. Initially, they do not know alpha and beta. At the end of each period, they observe the market return and their own returns and have to decide whether they should actively trade or passively invest in the next period. Ultimately, in the last period, uncertainty is resolved and they actively trade only if they have a positive alpha. Before then, they have to trade to learn about their alpha. This model generates predictions consistent with the evidence highlighted above: active trading is sensitive to both alpha and factor exposure performance. The model time line is presented in figure 1 and the formal solution of the model is derived in appendix.

2.1 Model set up

Individuals are risk neutral[1] and live for three periods. At the beginning of period 1, they have an initial wealth of 1 to invest in the stock market. At each period t individual i gets returns $1 + R_{it}$. Since R_{it} is small[2], I make the simplifying assumption that individual i maximizes:

$$E(\sum_{t=1}^{3} R_{it}) = \sum_{t=1}^{3} E(R_{it}) \tag{1}$$

Individual i's returns are characterized by factor exposure performance (beta) and excess performance (alpha). Beta is assumed to be constant across three periods, consistently with evidence that retail traders usually focus on a limited number of stocks with similar characteristics. Results would be unaffected if exposure was correlated over time. I provide evidence in that this is indeed the case in the empirical section of this paper.

Hence the exposure of her portfolio to the market factor at time t is measured by:

[1]Preliminary computations show that results are unaffected in a CARA or CRRA framework

[2]In the empirical sections of the paper, monthly returns are used

$$\beta_i \sim N(1, \sigma_\beta)$$

Individual i's alpha is also assumed to be fixed over time. Results would be unaffected if ability was correlated over time. Hence individual i's ability is given by:

$$\alpha_i \sim N(0, \sigma_\alpha)$$

α_i and β_i are independent.

The market factor return at time t which is called M_t:

$$M_t \sim N(0, \sigma_M)$$

M_t and M_{t+1} are independent.

To invest her wealth in the stock market, individual i chooses each period between:

- A fund which returns the market exposure performance of her portfolio :$\beta_i M_t$
- Active trading which returns the market exposure performance of her portfolio as well as alpha, the excess performance which she is able to generate: $\alpha_i + \beta_i M_t$

At the end of each period t, individual i 's information set, θ_{it}, contains the history of realizations of M_t and R_{it}.

Hence uncertainty on α_i and β_i is resolved at the end of the second period if individual i has actively traded at least once: she just has to solve a system of two equations with two unknown.

I present the time line of the model in figure 1. At each node, individual i chooses between actively trading (arrows going up) or passively investing (arrows going down) depending on her information set (described in boxes).

2.2 Solving the model

As apparent in figure 1, this model may be solved backward for the decision at each node, starting from period 3. I solve it in appendix and present the main intuitions here.

Individual investors always trade in period 1 to seize the option value of actively trading. In other words, there is more upside from trading that not trading in period 1: as you trade in period 1, you obtain more information about your market exposure and your alpha. Just like in any one-armed bandit problem, there is a value to exploration that drives all individual investors into trading in period 1.

In period 2 individual i actively trades only if her expectation of alpha conditional on the information she obtained from trading in period 1 is positive. From her active trading in period 1, she observes the market return, m_1 and her own active trading return r_{i1}. She knows that r_{i1} is the sum of her alpha plus her beta times m_{i1}. She also knows that whether or not she trades in period 2, she will observe m_2 and r_{i2} after trading in period 2, so that she will be able to infer her true alpha and trade accordingly in period 3. Hence whether or not she trades in period 2 will not affect her decision for period 3. Hence she trades in period 2 only if her expected return from doing so is larger than passively invest, that is if her expectation of alpha conditional on her information set at time 1, $E(\alpha_i/\theta_{i1})$ is superior to 0.

Finally, in period 3, uncertainty about α_i and β_i is resolved: since individual i has actively traded for at least one period she just has to solve a system of two equations with two unknowns to compute α_i and β_i . Hence positive alpha individual investors actively trade in period 3 while negative alpha individual investors passively invest.

2.3 Predictions on the sensitivity of active trading to past performance

In this paragraph I show that the simplified model presented above generates predictions consistent with the empirical results presented above. In particular, I focus on the decision that individual investors take at the beginning of period 2, after having observed market returns and their own active trading returns in period 1. At this point, individuals i has observed the realizations of the market $m1$ and her own return r_{i1}. She decides to actively trade in period 2 only if:

$$E(\alpha_i/m_1, r_{i,1}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2\sigma_\beta^2}(r_{i1} - m_1) > 0$$

I average this expression across groups and plot it as a function of m_1. I derive the following predictions both analytically in appendix and graphically in figures 2, 3 and 4, by using sample estimates of σ_α and σ_β.

Prediction 1: individual investors active trading decision is sensitive to their past performance.

Intuitively, for any realization m_1, individual investors who obtain a performance $r_{i1} > 0$ are more likely to have high alpha. Hence they are more likely to have $E(\alpha_i/m_1, r_{i1}) > 0$ and hence to trade in period 2. Figure 2 presents, for each realization m_1 of M_1, the average of $E(\alpha_i/m_1, r_{i1})$ for (i) individuals who experienced positive performance and (ii) individuals who obtained negative performance in period 1. It is clear that on average, individual investors who obtained positive performance will trade in period 2 while others won't.

Prediction 2: individual investors active trading decision is sensitive to their alpha.

Intuitively, individual investors with higher alpha are more likely to have $E(\alpha_i/m_1, r_{i,1}) > 0$ and hence to trade in period 2. Figure 3 presents, for each realization m_1 of M_1, the average of $E(\alpha_i/m_1, r_{i1})$ for (i) individuals who have a high alpha and (ii) individuals who have a negative alpha. It is clear that on average, individual investors who have a high alpha will trade in period 2 while others won't.

Prediction 3: individual investors active trading decision is sensitive to their factor exposure performance.

Recall that individual investors know nothing about their β_i to start with, but the distribution of β_i which is normal and centered around 1. Suppose they experience a very large positive market return m_1 in period 1. Investors with high β_i will obtain a very high $r_{i,1}$ while investors with low β_i will obtain a very low r_{i1}. Then investors with high

β_i are more likely than low β_i to have $E(\alpha_i/m_1, r_{i1}) > 0$. Hence high β_i are on average more likely than low β_i to actively trade in period 2 in this case, regardless of their true α_i. Figure 4 presents, for each realization m_1 of M_1, the average of $E(\alpha_i/m_1, r_{i1})$ for (i) individuals who have a beta larger than 1 and (ii) individuals who have beta lower than 1. It is clear that on average, individual investors who have a high (low) beta will actively trade in period 2 when m_1 has been positive (negative).

3 Defining individual investors' active trading and performance

In this section, I lay out the methodology used to measure active trading and individual investors active trading performance.

3.1 Measuring individual investors activity

This paragraph presents the way active trading is measured in the rest of this paper.

Identifying active trading from standard buy-and-hold strategies is a non trivial task. The literature has used different method to do so, such as for instance restricting the analysis to round-trip trades Linnainmaa (2011). Instead, I identify active trading using the "Differed Settlement Service" (henceforth "SRD") a specific feature of the French stock exchange (Euronext) and aimed at individual investors to enable them to initiate long position or short positions on a list of eligible securities only putting a portion of the value of the position forward, with a settlement of positions at the end of the month. In other words, the main reasons why an individual might use this service is the ability to short sell and the ability to lever up. The SRD is a service that brokers may or may not offer to their clients and which comes with related fees. The online broker which provided the data used in this paper has been offering this service since it was launched. Since individual investors posting trades on the SRD have to pay a fee to use the service, I am confident that only investors who are willing to actively trade will self select into this service. In particular, the SRD is widely used among individual investors. In the data, the SRD is used for 46% of stock trades and 64% of volume of French stocks.

Euronext launched the SRD in September 2000. As detailed in Foucault et al. (2011), the SRD was introduced as part of a reform of the French stock exchange related to European harmonization. Before September 2000, individual investors could trade large stocks on a future markets and small stocks on the spot market. After September 2000, individual investors can trade all stocks spot and can use the SRD service to take positions on eligible stocks. To be eligible to the SRD, a stock must either have a market cap larger than 1 billion euros and a daily volume of at least 1 million euro, or belong to the SBF 120, the French index of the 120 largest stocks. There were 120 eligible stocks initially, and 233 as of 2010. Individual investors using the SRD can take positions until the fifth business day before the end of the month. When an individual reaches the end of the month, either she has liquidated all here positions and she will receive the difference between the sale and the purchase prices. Either she still has some nonzero positions in various stocks and she can choose to (i) liquidate these positions or (ii) roll them over to the next month in exchange of a “roll-over fee”.

The fees that brokers usually charge has two components on top of usual brokerage fees. First, 0.02% to 0.03% are charged each day on the amount held through the SRD. Second, brokers charge a roll-over fee of 0.2% to 0.3% on the amount that individual investors wish to roll-over to the next month.

The amount of leverage that individual investors can take depends on their outstanding portfolio, which serves as a collateral to their purchases through the SRD. The rules for the collateral are set by the French regulator (AMF); however each financial intermediary is free to request higher minimum collateral rates. Individual investors are allowed to lever up to five times the amount of cash and French government bonds and monetary funds they hold, four times the amount of bonds (traded on any EU regulated market, other European government bonds and bond funds) they hold and two and a half times the stocks (traded on any EU regulate market) and European equity funds they hold.

Restricting the sample to SRD trades is particularly well suited to capture active trading for a variety of reasons. First, investors using the SRD are very unlikely to do so for liquidity or hedging motives as it comes with additional fees. Hence we are left exclusively with active traders intending to generate performance by exploiting private information or acting as liquidity providers by taking leverage or shorting stocks. Moreover, the monthly settlement procedure alleviates liquidity constraints, since investors do not need to actually pay for the assets they trade before the date of the monthly settlement. This mitigates the concern that inferences may be biased by the fact that past performance influences subsequent trading by relieving or increasing liquidity constraints. Also, the monthly settlement procedure generates a clear sequence of actions and outcomes which is ideally suited to test any learning model. At the end of each month, retail investors may close their positions or roll them over in exchange for a "roll-over fee". Hence there is no doubt that individual investors using the SRD do analyze their positions and performance at the end of each month to take subsequent decisions. Finally, in figure 5, I present the investment objective of 833 individuals in the dataset either using the SRD service or not using it. SRD traders answer "Directly investing in the stock market" approximately 70% of the time, which is twice as often as non SRD traders. This confirms that the main characteristic of SRD traders is the desire to actively trade in the stock market.

I track the "active trading" career of individuals from the first day they start using the SRD. I stop tracking the "active trading" career of individuals if they do not post any trade using the SRD for three successive months. In other words, I am not keeping in the sample months during which an individual investor uses the SRD after she has not posted any trades using the SRD for three successive months. However, two thirds of individual investors in the sample never use the SRD again once they stop trading for three successive months.

I measure the intensity of individual investor i 's trading activity in month t using a variety of variables: the log of the number of orders, the log of the eur volume traded, the log euro volume per stock traded, the excess volume purchased over volume sold normalized by total volume, the log of the average order size and a continuation dummy equals to one if individual i is active in month $t+1$ or if individual i stops trading.

3.2 Measuring individual investors performance

Measuring investors' stock performance is uneasy for at least three reasons. First, the horizon at which the performance should be measure is unclear and largely varies across papers. Second, it is unclear how performance should be computed when investors hold on to their positions and do not unwind them, since the time when positions are liquidated contributes to the overall performance of the trade. Third, investors may build up and liquidate positions in a sequential way which makes it difficult to know which entry price and exit price to consider for the trade.

The framework I'm using enables me to handle the first point. The horizon of a trader using the SRD service is clearly the end of the month, where she'll have to decide whether to roll-over her position (at a cost) or not. To handle the second and third point, I apply the approach used by Linnainmaa (2011) to measure the monthly performance of individual investors in my sample.

For each stock s traded by individual i in month t, I computed its performance $\pi_{i,s,t}$ as follows:

$$\pi_{i,s,t}$$
$$= p^s_{i,s,t}/p^b_{i,s,t} - 1, \text{ if } v^s_{i,s,t} = v^b_{i,s,t}$$
$$= (p^s_{i,s,t}/p^b_{i,s,t} - 1) \times v^s_{i,s,t}/v^b_{i,s,t} + (p^c_{s,t}/p^b_{i,s,t} - 1) \times (v^b_{i,s,t} - v^s_{i,s,t})/v^b_{i,s,t}, \text{ if } v^s_{i,s,t} < v^b_{i,s,t}$$
$$= (p^s_{i,s,t}/p^b_{i,s,t} - 1) \times v^b_{i,s,t}/v^s_{i,s,t} + (p^s_{i,s,t}/p^c_{s,t} - 1) \times (v^s_{i,s,t} - v^b_{i,s,t})/v^s_{i,s,t}, \text{ if } v^s_{i,s,t} > v^b_{i,s,t}$$

where n is the number of stocks investor i trades in month t, $p^b_{i,s,t}$ and $p^s_{i,s,t}$ are the investor's average purchase and sale prices in stock s, where the purchase and sale price of stock s in day d is the closing price of stock s in day d. $v^b_{i,s,t}$ and $v^s_{i,s,t}$ are the number of shares purchased and sold, and $p^c_{s,t}$ is the stock's price on the last day of the trading month. If an investor buys and sells different amounts, the remaining position is marked-to-market at the end of the trading month.

From there I compute an unweighted and a weighted measure of individual i 's performance in month t , $\pi_{i,t}$ and $\pi_{i,t}^{w}$ as

$$\pi_{i,t} = \frac{1}{n}\sum_{s=1}^{n}\pi_{i,s,t}$$

$$\pi_{i,t}^{w} = \sum_{s=1}^{n}\frac{vol_{i,s,t}}{vol_{i,t}}\pi_{i,s,t}$$

where $vol_{i,t}$ and $vol_{i,s,t}$ are respectively the total euro volume and the euro volume of stock s traded in month t by individual i. In the paragraphs that follow, I will only consider $\pi_{i,t}$ to save notations. But all empirical results will be run using both weighted and unweighted measures of performance.

At the end of each trading month, if they have a still unwound long (short) position in a stock, investors have the choice between obtaining delivery (payment) of the stock or rolling the position over to the next trading month. One limitation of the data is that I can not observe whether a position is rolled-over. What I observe, though is whether an investor pays any roll-over fees in any given month. Hence, I consider that investors (not) paying roll-over fees in a given month roll-over all (none of) their positions to the following month. Rolled-over positions are then valued at the closing price of the first day of the next month and included in the computation of the next month performance.

3.3 Measuring the alpha and factor exposure performance of individual investors

This paper intends to isolate the performance of active trading by individual investors related to usual risk factors: Mkt, the market return minus the risk free rate, SMB (the excess return of small firms) and HML (the excess return of value firms). The method used here compares the performance of an individual i in month t trading n stocks s to the performance she would have obtained by trading n indices replicating the exposure of each stock s to each of the three factors $f \in \{Mkt, SMB, HML\}$ instead. I do this in two steps. I first compute the exposure (beta) of each stock s in month t to each factor f. Then I compute the performance individual i would have obtained if she had traded n indices replicating the returns of each risk factor instead of n stocks.

3.3.1 Computing risk factor exposure for each stock

I first construct the series of daily returns of each of the three factors. Mkt is the daily value weighted average return on all stocks traded by individual investors, minus the interest rate on French 10 year treasury bonds. SMB is computed by sorting firms according to the past year market capitalization. Big firms are the 20% largest firms and small firms are the 20% smallest ranked in the last month of the previous year. To determine SMB, I subtract, each month, the value weighted monthly returns of the largest firms from the value weighted monthly returns of the 20% largest firms. To compute HML, I sort firms by past year book-to-market value of assets. “Value firms” are firms with the 20% highest book-to-market in the previous year, and “glamor,” firms with the lowest 20%. HML is the difference in value-weighted monthly returns between the value and the glamor portfolio.

Then in each month t, for each stock s, I run the following Fama French three factor model:

$$R_{s,d} = \beta_{s,t}^{Mkt} \times Mkt_d + \beta_{s,t}^{SMB} \times SMB_d + \beta_{s,t}^{HML} \times HML_d + \epsilon_{s,d}$$

where $R_{s,d}$ is the return of stock s minus the risk free rate in day d, Mkt_d, SMB_d and HML_d are the daily returns of each of the three factors. The coefficient obtained for each factor f, $\beta_{s,t}^{f}$, measures the sensitivity of the returns of stock s to factor f as measured in month t.

3.3.2 Replicating performance with factor indices

Then for each stock s and each factor $f \in \{Mkt, SMB, HML\}$, I compute $\pi_{i,s,t}^{f}$, the profit individual investor i would have realized in month t if instead of trading stock s

she had traded an index replicating the returns of factor f.

$\pi^{f}_{i,s,t}$

$= i^{s}_{i,f,t}/i^{b}_{i,f,t} - 1$, if $v^{s}_{i,s,t} = v^{b}_{i,s,t}$

$= (i^{s}_{i,f,t}/i^{b}_{i,f,t} - 1) \times v^{s}_{i,s,t}/v^{b}_{i,s,t} + (i^{c}_{f,t}/i^{b}_{i,f,t} - 1) \times (v^{b}_{i,s,t} - v^{s}_{i,s,t})/v^{b}_{i,s,t}$, if $v^{s}_{i,s,t} < v^{b}_{i,s,t}$

$= (i^{s}_{i,s,t}/i^{b}_{i,s,t} - 1) \times v^{b}_{i,s,t}/v^{s}_{i,s,t} + (i^{s}_{i,s,t}/i^{c}_{s,t} - 1) \times (v^{s}_{i,s,t} - v^{b}_{i,s,t})/v^{s}_{i,s,t}$, if $v^{s}_{i,s,t} > v^{b}_{i,s,t}$

where n is the number of stocks investor i trades in month t, $i^{b}_{i,f,t}$ and $i^{s}_{i,f,t}$ are the investor's average purchase and sale prices in the index replicating the performance of factor f, $v^{b}_{i,s,t}$ and $v^{s}_{i,s,t}$ are the number of shares purchased and sold of stock s, and $i^{c}_{f,t}$ is the index's price on the last day of the month. If an investor buys and sells different amounts, the remaining position is marked-to-market at the end of the trading month.

From there I get for each individual i in each month t its factor exposure performance for each factor $f \in \{Mkt, SMB, HML\}$, $\beta\pi^{f}_{i,t}$, computed as:

$$\beta\pi^{f}_{i,t} = \frac{1}{n}\sum_{s=1}^{n} \beta^{f}_{s,t-1\times}\pi^{f}_{i,s,t}$$

I also compute the weighted factor exposure performance for each factor f using the same weights as in paragraph 2.2, i.e. the ratio of the euro volume traded of stock s in month t to the total euro volume traded in month t.

For each individual i in month t, I compute the average beta of individual investor i's trades in month t with respect to each of the three factors f , $\beta^{f}_{i,t}$, as follows:

$$\beta^{f}_{i,t} = \frac{1}{n}\sum_{s=1}^{n} \beta^{f}_{s,t-1}$$

I also compute a weighted version of that beta for each factor f using the same weights as in paragraph 2.2, i.e. the ratio of the euro volume traded of stock s in month t to the total euro volume traded in month t.

Finally, I recover the residual performance of each individual i ("alpha"), in each month t stripped from the factor exposure performance, $\alpha_{i,t}$ as follows:

$$\alpha_{i,t} = \pi_{i,t} - \beta\pi^{Mkt}_{i,t} - \beta\pi^{SMB}_{i,t} - \beta\pi^{HML}_{i,t}$$

It should be noted that alpha is not a pure measure of excess performance and also absorbs some noise. It should be interpreted as the share of individual i's performance not attributable to systematic risk factors. I also compute the weighted alpha using the same weights as in paragraph 2.2, i.e. the ratio of the euro volume traded of stock s in month t to the total euro volume traded in month t.

In the empirical part that follows, I will measure the sensitivity of individual i active trading in month t to the various components of her performance.

4 Data

I use a 10 year long, unique and large sample of French retail traders provided by a leading European broker in personal investing and online trading.

From 1999 to 2010, this broker accounted for an average 15% of online brokers trades on Euronext Paris, which collectively represented 14% of all trades in the market[3]. This broker provided the complete daily trading records of their active retail client base from January 1999 to December 2010. For a sub-sample of 833 traders, the answers to a regulatory ("Mifid") questionnaire are available, with information regarding wealth and investment objectives.

To identify the decision to actively trade, I use the "Differed Settlement Service" (henceforth "SRD") a specific feature of the French stock exchange (Euronext), launched in September 2000 and aimed at individual investors. When restraining individual investors actively trading using the SRD, I am left with 14151 individual investors.

I obtain exhaustive and reliable market data from EUROFIDAI, which enables me to compute accurate stock and factor returns. I obtain book-to-market ratios from Datastream.

Summary statistics are presented in table 1. There are 14151 distinct individual investors actively trading in 7.7 successive periods on average. On average, these individual

[3]According to Acsel, an association of online brokers (see http://www.associationeconomienumerique.fr/) which collects monthly data on online trading

investors post 6 trades per month using the SRD, with an average volume traded of 21590 euros and an average trade size of 3463 euros. Note that there are very few short positions observed in the dataset, although the cost of taking a short position through the SRD is symmetric to the cost of taking a long position. Hence individual investors seem to use the SRD to take levered position rather than take sort positions. Note that there is no way to make sure that individual investors in this sample are not using another broker before, after or contemporaneous to their investment career as observed in this sample.

5 Sensitivity of trading to past performance

In this section I first check that, consistent with existing literature, individual investors' active trading in the sample is sensitive to their past performance. Then I ask to what extent the activity of individual investors is sensitive to the various components of their performance, alpha and factor exposure performance.

5.1 Individual investors trading is sensitive to past performance

The first test I run intends to check that, consistent with previous literature, individual investors' active trading is sensitive to past performance. The following regression is run:

$$T_{i,t+1} = \lambda_1 \pi_{i,t} + \lambda_2 P_{i,t} + \kappa_i + \delta_e + \mu_t + \epsilon_{i,t}$$

where $T_{i,t+1}$ is a measure of trading activity of individual i in month t. I consider successively the log of the number of orders, the log of the eur volume traded, the log euro volume per stock traded, the excess volume purchased over volume sold normalized by total volume, the log of the average order size, and a dummy equals to one if individual i is active in month $t+1$ or if individual i stops trading. $\pi_{i,t}$ is the performance of individual i in month t as computed in section 2, $P_{i,t}$ is the increase in the log eur value of individual i's portfolio in month t (including positions taken on the spot market) and κ_i, δ_e and μ_t are respectively individual, experience (the number of trading month since individual i

started active trading) and time fixed effects. Standard errors are clustered at the monthly level. The same regression is run with the weighted performance of individual i in month t where the performance on each stock traded by individual i in month t is weighted by the ratio of the euro volume traded of stock s in month t to the total euro volume traded in month t. Table 2 presents the results of this regression. All measures of trading activity are significantly positively correlated with past performance. A one standard deviation in performance increases the probability of continuation by 0.5%.

The second test intends to disentangle the sensitivity of trading to the various components of individual investors' performance. The following regression is run:

$$T_{i,t+1} = \lambda_1 \alpha_{i,t}$$

$$+\lambda_2 \beta\pi_{i,t}^{Mkt} + \lambda_3 \beta\pi_{i,t}^{SMB} + \lambda_4 \beta\pi_{i,t}^{HML}$$

$$+\lambda_5 \pi_{i,t}^{Mkt} + \lambda_6 \pi_{i,t}^{SMB} + \lambda_7 \pi_{i,t}^{HML} + \lambda_8 \beta_{i,t}^{Mkt} + \lambda_9 \beta_{i,t}^{SMB} + \lambda_{10} \beta_{i,t}^{HML} + \lambda_{11} P_{i,t} + \kappa_i + \delta_e + \mu_t + \epsilon_{i,t}$$

where $T_{i,t+1}$ is a measure of trading activity of individual i in month . I consider successively the log of the number of orders, the log of the eur volume traded, the log euro volume per stock traded, the excess volume purchased over volume sold normalized by total volume, the log of the average order size, and a dummy equals to one if individual i is active in month $t+1$ or if individual i stops trading. $\beta\pi_{i,t}^{Mkt}$, $\beta\pi_{i,t}^{SMB}$and $\beta\pi_{i,t}^{HML}$ are the returns obtained from the exposure of individual i's trades to the three risk factors. The third component of the regression includes the following controls. $\pi_{i,t}^{Mkt}$, $\pi_{i,t}^{SMB}$and $\pi_{i,t}^{HML}$ are the returns on the indices replicating the risk factors. $\beta_{i,t}^{Mkt}$ $\beta_{i,t}^{SMB}$and $\beta_{i,t}^{HML}$ are the average exposure of the stocks traded by individual i to each of the three risk factors. $P_{i,t}$ is the increase in the log eur value of individual i's overall portfolio in month t (including positions taken on the spot market) and κ_i, δ_e and μ_t are respectively individual, experience (the number of trading month since individual i started active trading) and time fixed effects. Standard errors are clustered at the monthly level. The same regression is then run with variables weighted by the ratio of the euro volume traded of stock s in month t to the total euro volume traded in month t.

The coefficients of interest are λ_1, λ_2, λ_3 and λ_4. Results are presented in table 3. Surprisingly, perhaps, all measures of investor trading strongly react to both alpha and factor exposure performance. Coefficients on factor exposure performance are even slightly higher than coefficients on alpha. Results are of the same magnitude than those in table 2.

5.2 Do investors time the market?

This section investigates whether the result obtained in the previous section could be explained by individual investors' market timing or forecasting ability. Suppose that factor returns are correlated from one period to another. Knowing this, individual investors in month t could guess what factor returns will be in month $t+1$ and adjust their factor exposure accordingly to benefit from higher factor exposure performance. For instance, suppose that market returns are auto-correlated. Hence if you observe high market returns in month t you can extrapolate that market returns will be high in month $t+1$ and decide to increase your exposure to market returns and trade more in month $t+1$.

First, I check whether factor returns are auto-correlated. To do so, I compute the monthly auto-correlation in the returns of each of the three risk factors: Mkt, SMB and HML. It appears that Mkt and SMB are not auto-correlated and that HML is weakly auto-correlated. These correlations are presented in table 4. From there, it seems implausible that any individual can reliably infer month $t+1$ factor returns by observing month t factor returns.

However, individuals may be able to forecast factor returns. Hence I check whether their factor exposure moves in the same direction as factor returns. I run the following regression for each factor $f \in \{Mkt, SMB, HML\}$:

$$R_t^f = \lambda_1 \beta_{i,t}^f + \kappa_i + \delta_e + \epsilon_{i,t}$$

where R_t^f is the return of risk factor f in month t. κ_i and δ_e are respectively individual and experience (the number of trading month since individual i started active trading) fixed effects. Standard errors are clustered at the monthly level. Results are presented in table 5. The exposure to the market is negatively correlated to the market factor returns, while the exposure to the two other factors are uncorrelated with these factors. Hence individual investors do not seem to strategically adjust their factor exposure to increase their performance.

Finally, several recent papers (Dorn and Huberman, 2010; Kumar et al., 2011) have established that households keep trading a subset of stocks with similar characteristics over time. I check that this translates into a persistence of the characteristics of retail investors actively traded portfolio. I run the following regression for each factor $f \in \{Mkt, SMB, HML\}$:

$$\beta^f_{i,t+1} = \lambda_1 \beta^f_{i,t} + \delta_e + \mu_t + \epsilon_{i,t}$$

where $\beta^f_{i,t+1}$ is the exposure of individual i to factor f in month t. δ_e and μ_t are respectively experience (the number of trading month since individual i started active trading) and time fixed effects. Standard errors are clustered at the monthly level. Results presented in table 6 show that the exposure to risk factors is quite stable through time. The auto-correlation coefficient on alpha is positive though not significant, probably because the measure of alpha includes some noise as mentioned above.

6 Learning dynamics

In this section, I highlight and test three additional predictions of the model presented above. These predictions are specific to this model and would be harder to justify in an story based on overconfidence. First, I show that the sensitivity of trading to past performance decreases with the absolute value of factor returns. Second, I check whether the sensitivity of trading to past performance evolves through time as it is described in the model: trading should become less sensitive to the three risk factor performance and more sensitive to the residual performance. Third, I check whether the speed at which individuals learn and decide to quit active trading is influence by their early experience.

Individuals with extreme risk factors experience, for instance individuals with low market betas experiencing low stock market returns early in their life keep actively trading for a longer period of time than individuals with high market betas and low stock market returns, everything else equal.

Prediction 4: individual investors' active trading sensitivity to past performance is decreasing in absolute factor returns.

In the simplified trading model presented above, individual investors decide whether to actively trade or not in period 2 if:

$$E(\alpha_i/m_1, r_{i,1}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2\sigma_\beta^2}(r_{i1}\text{-}m_1)¿0$$

This expectation is increasing in the value of r_{i1},the performance in period 1. However, when m_1 has been very high or very low, the sensitivity of the expectation to r_{i1} is lower. Intuitively, if the market return in period 1 has been close to zero, individual investor i will more easily infer alpha from the performance she obtained in period 1. Hence a small but positive performance in period 1 will signal a positive alpha and conversely. However, if the market return in period 1 has been very large or very low, individual i has a much harder time inferring alpha from her performance in period 1. Hence her decision is relatively less sensitive to past performance. This prediction can be tested quite easily. I run the following regression in the panel of individual investors:

$$T_{i,t+1} = \lambda_1\pi_{i,t} + \lambda_2 AbsR_t^{Mkt} \times \pi_{i,t} + \lambda_3 AbsR_t^{SMB} \times \pi_{i,t} + \lambda_4 AbsR_t^{HML} \times \pi_{i,t} +$$
$$\lambda_5 AbsR_t^{Mkt} + \lambda_6 AbsR_t^{SMB} + \lambda_7 AbsR_t^{HML} + \lambda_8 P_{i,t} + \kappa_i + \delta_e + \epsilon_{i,t}$$

where $T_{i,t+1}$ is a measure of trading activity of individual i in month. I consider successively the log of the number of orders, the log of the eur volume traded, the log euro volume per stock traded, the excess volume purchased over volume sold normalized by total volume, the log of the average order size, and a dummy equals to one if individual i is active in month $t+1$ or if individual i stops trading. $\pi_{i,t}$ is the performance of individual i in month t as computed in section 2, $AbsR_t^f$ is the absolute value of the return of risk factor f in month t, $P_{i,t}$ is the increase in the log eur value of individual i's portfolio in month t, and κ_i and δ_e are respectively individual, experience . Standard errors are in parenthesis and are clustered at the monthly level. In Panel B, the same regression is run with the weighted performance of individual i in month t where the performance on each stock traded by individual i in month t is weighted by the ratio of the euro volume traded of stock s in month t to the total euro volume traded in month t. Results in table 7 show that consistent with the intuition highlighted in the model, individual investors' trading activity seem to be less sensitive to past performance when past factor returns have been large in absolute value.

Prediction 5: individual investors' active trading sensitivity to alpha decreases with experience while individual investors' active trading decision sensitivity to factor exposure performance decreases.

In the simple three period model presented above, individual i's choice to actively trade in period 2 is sensitive to past factor exposure performance as well as to her alpha. In period 3, her choice to actively trade is fully sensitive to her alpha, but not to her past factor exposure performance anymore. Hence we should observe that the sensitivity of trading activity to past factor exposure performance decreases through time while the sensitivity of trading activity to alpha increases. I define experience as the number of months since individual i started actively trading. Then I run the following regression in the cross-section of actively trading individual investors at each experience month e:

$$T_{i,e+1} = \lambda\alpha_{i,e} + \epsilon_{i,e}$$

$$T_{i,e+1} = \lambda\gamma_{i,e} + \epsilon_{i,e}$$

where $T_{i,e+1}$ is a dummy equals to one if individual i is active in month $e+1$ or zero if individual i stopped trading. $\alpha_{i,e}$ is the alpha of investor i in experience month e and $\gamma_{i,e} = \pi_{i,e} - \alpha_{i,e}$ is the aggregate factor exposure performance over all three risk factors of individual i in experience month e.

I then plot the coefficients obtained in these regressions and confidence intervals in figure 6. I keep the first four months of experience after the initial trading month because half of investors in the sample stop trading on the SRD after 4 months.

Prediction 6: individual investors with high factor exposure performance early in their investment life keep on actively trading longer and exit later, everything else equal.

Another prediction of the model regards the speed at which individual investors decide to stop actively trading. In the model presented above, investors with high alpha are more likely to actively trade. Moreover, high (low) beta investors are more likely to keep on actively trading in period 2 when they have experienced high (low) factor returns in period 1, independently of their alpha. I run the following regression on the sample of investors for which I observed an exit before December 2010:

$$S_i = \lambda_1 \alpha_{i,1} + \lambda_2 \gamma_{i,1}$$

where S_i is the inverse of the number of successive active trading periods of individual i, $\gamma_{i,1} = \pi_{i,1} - \alpha_{i,1}$ is the aggregate factor exposure performance over all three risk factors of individual i in the first month she trades. The regression is run with unweighted and weighted measures of performance. Results presented in table 8 provide some evidence, consistent with model predictions, that the initial factor exposure performance of individual investors has an impact on the length of their active trading career and the speed at which they stop actively trading.

7 Conclusion

This paper develops the idea that households have an imprecise knowledge of their portfolio's exposure to systematic risk and that this leads them to make investment mistakes. This idea is tested in the context of the decision to actively trade on the stock market rather than passively invest.

I use a 10 year long, unique and large sample of French retail traders provided by a leading European broker in personal investing and online trading. To identify the decision to actively trade, I use a specific feature of the French stock exchange (Euronext).

Using a number of measures of individual investors trading activity, I observe that individual investors increase their active trading activity following good performance. More interestingly, I carefully split individual investors performance into (i) excess performance and (ii) performance related to the exposure of their trades to usual risk factors such as the market premium, the excess returns on small stocks and the excess returns on value stocks and show that trading activity reacts to both. I ask whether this can be explained by the market timing or forecasting ability of individual investors to predict the returns of risk factors and to modify their exposure to those risk factors accordingly. Instead I find that the exposure of individual investors trades to risk factors remains remarkably stable.

I present a simple trading model that accounts for these findings. In the model, individual investors have to decide whether to passively invest or actively trade with limited information on their alpha and beta. The model also generates additional predictions regarding learning dynamics:(i) active trading sensitivity to past performance is smaller when factor returns have been large in absolute value, (ii) the sensitivity of active trading to alpha and factor exposure performance respectively increases and decreases as individual investors learn, and (iii) individuals with high factor exposure performance early in their active investment career stay active longer than individuals with low factor exposure performance early in their active investment career, independently of their respective alpha. I provide some empirical evidence supporting these three additional predictions.

Since some individuals investors lose money by actively trading for too long despite a negative alpha or by quitting too early despite a positive alpha, understanding how they take their trading decision is important: if they trade to learn, then tools properly designed to help households figure out their risk exposure would probably save them time and money. Moreover, whether the fact that individual investors are ex ante uncertain about their ability and risk exposure is the result of financial illiteracy or of the cost associated with computing factor exposure is an important question.

The mechanism highlighted in this paper may be insightful in the context of other households financial decisions. In particular, it may well apply to households investments in mutual funds, a topic that I am currently exploring.

References

Agarwal, Sumit, John C. Driscoll, Xavier Gabaix, and David Laibson, "Learning in the Credit Card Market," *NBER Working Paper*, February 2008, (13822).

Barber, B M, Y T Lee, Y J Liu, and T Odean, "Just How Much Do Individual Investors Lose by Trading?," *Review of Financial Studies*, 2006, *22* (2), 609–632.

Barber, Brad M and Terrance Odean, "Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors," *The Journal of Finance*, 2000, *55* (2), 773–806.

_ and _ , "Online Investors: Do the Slow Die First?," *Review of Financial Studies*, 2002, *15* (2), 455–487.

Calvet, Laurent E, John Y Campbell, and Paolo Sodini, "Down or Out: Assessing the Welfare Costs of Household Investment Mistakes," *Journal of Political Economy*, 2006, *115* (5), 707–747.

_ , _ , and _ , "Fight Or Flight? Portfolio Rebalancing by Individual Investors," *Quarterly Journal of Economics*, 2009, *124* (1), 301–348.

_ , _ , and _ , "Measuring the Financial Sophistication of Households," *American Economic Review*, 2009, *99* (2), 393–398.

Chevalier, Judith and Glenn Ellison, "Risk Taking by Mutual Funds as a Response to Incentives," *Journal of Political Economy*, 1997, *105* (6), 1167–1200.

_ and _ , "Career Concerns of Mutual Fund Managers," *Quarterly Journal of Economics*, 1999, *114* (2), 389–432.

Chiang, Y M, D Hirshleifer, Y Qian, and A E Sherman, "Do Investors Learn from Experience? Evidence from Frequent IPO Investors," *Review of Financial Studies*, 2011, *24* (5), 1560–1589.

Choi, James J, David Laibson, Brigitte C Madrian, and Andrew Metrick, "Reinforcement Learning and Savings Behavior.," *The Journal of finance*, 2009, *64* (6), 2515–2534.

Coval, Joshua D, David A Hirshleifer, and Tyler Shumway, "Can Individual Investors Beat the Market ? Can Individual Investors Beat the Market ?," *Social Science Research*, 2005, *1001* (04), 1–37.

Dorn, Daniel and Gur Huberman, "Preferred risk habitat of individual investors," *Journal of Financial Economics*, 2010, *97* (1), 155–173.

Foucault, Thierry, David Sraer, and David J Thesmar, "Individual Investors and Volatility," *Journal of Finance*, 2011, *LXVI* (4), 1369–1406.

French, Kenneth R, "Presidential Address: The Cost of Active Investing," *The Journal of Finance*, 2008, *63* (4), 1537–1573.

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

Glaser, M and M Weber, "Why inexperienced investors do not learn: They do not know their past portfolio performance," *Finance Research Letters*, 2007, *4* (4), 203–216.

Glaser, Markus and Martin Weber, "Overconfidence and trading volume," *The Geneva Risk and Insurance Review*, 2007, *32* (1), 1–36.

_ and _ , "Which past returns affect trading volume?," *Journal of Financial Markets*, 2009, *12* (1), 1–31.

Greenwood, Robin and Stefan Nagel, "Inexperienced investors and bubbles," *Journal of Financial Economics*, 2009, *93* (2), 239–258.

Grinblatt, Mark and Matti Keloharju, "The investment behavior and performance of various investor types: a study of Finland's unique data set," *Journal of Financial Economics*, 2000, *55* (1), 43–67.

— **and** — , “Sensation Seeking, Overconfidence, and Trading Activity,” *The Journal of Finance*, 2009, *64* (2), 549–578.

— **,** — **, and Juhani T Linnainmaa**, “Do Smart Investors Outperform Dumb Investors ?,” *Social Science Research*, 2009, (09).

Kaustia, Markku, Eeva Alho, and Vesa Puttonen, “How Much Does Expertise Reduce Behavioral Biases? The Case of Anchoring Effects in Stock Return Estimates,” *Financial Management*, 2008, *37* (3), 391–412.

Kumar, Alok, Jeremy Page, and Oliver Spalt, “Investor Clienteles and Habitat-Based Return Comovements,” *AFA 2011 Denver Meetings Paper.*, 2011.

Linnainmaa, J T, “Why Do (Some) Households Trade So Much?,” *Review of Financial Studies*, 2011, *24* (5), 1630–1666.

List, John A, “Does Market Experience Eliminate Market Anomalies?,” *Quarterly Journal of Economics*, 2003, *118* (1), 41–71.

Lusardi, Annamaria and Olivia S Mitchell, “Planning and Financial Literacy: How Do Women Fare?,” *American Economic Review*, 2008, *98* (2), 413–417.

— **and Peter Tufano**, “Debt literacy, financial experiences, and overindebtedness,” *NBER working paper*, 2009, *54* (14808), 258.

Mahani, Reza and Dan Bernhardt, “Financial Speculators’ Underperformance: Learning, Self-Selection, and Endogenous Liquidity,” *The Journal of Finance*, 2007, *62* (3), 1313–1340.

Malmendier, Ulrike and Stefan Nagel, “Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?*,” *The Quarterly Journal of Economics*, 2011, *126* (1), 373–416.

Nicolosi, Gina, Liang Peng, and Ning Zhu, "Do individual investors learn from their trading experience?," *Journal of Financial Markets*, 2009, *12* (2), 317–336.

Pastor, Lubos and Pietro Veronesi, "Learning in Financial Markets," *Annual Review of Financial Economics*, 2009, *1* (1), 361–381.

Seru, A, T Shumway, and N Stoffman, "Learning by Trading," *Review of Financial Studies*, 2009, *23* (2), 705–739.

Stango, Victor and Jonathan Zinman, "Exponential Growth Bias and Household Finance," *The Journal of Finance*, 2009, *64* (6), 2807–2849.

Statman, M, S Thorley, and K Vorkink, "Investor Overconfidence and Trading Volume," *Review of Financial Studies*, 2006, *19* (4), 1531–1565.

Van Rooij, Maarten, Annamaria Lusardi, and R J M Rob Alessie, "Financial Literacy and Stock Market Participation," *NBER working paper*, 2007, *No. 13565* (April), 1–48.

Appendices

Maths appendix

Solving the model

In the following paragraphs, I solve for the optimal decision at each node of the tree, given the expected information set.

Period 3

In this paragraph I solve for the optimal decision of investor i whether or not to actively trade at the beginning of period 3. After period 2, either individual i has actively traded at least one time in period 1 and 2, or she has never actively traded before.

If she has actively traded once or twice in periods 1 and/or 2, she has enough information to discover α_i and β_i after period 2. Thus uncertainty is resolved. The expected payoff from actively trading in period 3 is given by $\alpha_i + \beta_i E(M_3)$ while the expected payoff from passively investing in period 3 is given by $\beta_i E(M_3)$. Hence individual i will actively trade if $\alpha_i > 0$ and passively invest if $\alpha_i \leq 0$.

If she has never actively traded in periods 1 and 2, individual i knows the value of β_i but she has no information about α_i. The payoff from actively trading is given by $E(\alpha_i) + \beta_i E(M_3) = \beta_i E(M_3)$ which equals the expected payoff from passively investing, $\beta_i E(M_3)$. Hence individual i is indifferent between actively trading and passively investing in period 3.

Period 2

In this paragraph I solve for the optimal decision of investor i whether or not to actively trade at the beginning of period 2. After period 1, either individual i has actively traded in period 1 or not.

If she has actively traded in period 1, she has observed the realizations r_{i1} and m_1 of R_{i1} and M_1 (Let θ_{i1}be her information set at that point). Moreover, she knows that whichever her decision to actively trade or passively invest in period 2, uncertainty will be resolved in period 3 so that she will trade only if $\alpha_i > 0$. Her decision in period 2 has no impact on her expected period 3 payoff. Hence individual i will actively trade if $E(\alpha_1/\theta_{i1}) > 0$ and passively invest if $E(\alpha_i/\theta_{i1}) \leq 0$.

If she has passively invested in period 1, she has observed the realizations $r_{i1}$and m_1 of R_{i1} and M_1,θ_{i1}. With respect to the beginning of period 1, she has no additional information regarding α_i. However, she knows the exact value of β_i. If she actively trades in period 2, uncertainty will be resolved in period 3 so that she will trade only if $\alpha_i > 0$. In this case, she expects to obtain $E(\alpha_i/\alpha_i > 0) + E(\beta_i M_3/\alpha_i > 0) = E(\alpha_i/\alpha_i > 0)$ if she actively trades in period 3 and $E(\beta_i M_3/\alpha_i \leq 0) = 0$ if she passively invests in period 3.

Hence individual i always actively trades in period 2 if she has not traded in period 1, so as to seize the opportunity to trade in period 3 when uncertainty is resolved.

In other words,

If individual i has actively traded in period 1

- The expected payoff from actively trading in period 2 is given by:

$$\{E(\alpha_i/\theta_{i1}) + E(\beta_i M_2/\theta_{i1})\}$$
$$+ \{P(\alpha_i/\alpha_i > 0)\,[E(\alpha_i/\alpha_i > 0) + E(\beta_i M_3/\alpha_i > 0)] + P(\alpha_i/\alpha_i < 0)E(\beta_i M_3/\alpha_i > 0)\}$$
$$= E(\alpha/\theta_{i1}) + \tfrac{1}{2}E(\alpha_i/\alpha_i > 0)$$

- The expected payoff from passively investing in period 2 is given by:

$$E(\beta_i M_2/\theta_{i1})$$
$$+ \{P(\alpha_i/\alpha_i > 0)\,[E(\alpha_i/\alpha_i > 0) + E(\beta_i M_3/\alpha_i > 0)] + P(\alpha_i/\alpha_i < 0)E(\beta_i M_3/\alpha_i > 0)\}$$
$$= \tfrac{1}{2}E(\alpha_i/\alpha_i > 0)$$

Hence she actively trades if $E(\alpha_i/\theta_{i1}) > 0$

If individual i has passively invested in period 1

- The expected payoff from actively trading in period 2 is given by :

$\{E(\alpha_i/\theta_{i1}) + E(\beta_i M_2/\theta_{i1})\}$
$+ \{P(\alpha_i/\alpha_i > 0)\,[E(\alpha_i/\alpha_i > 0) + E(\beta_i M_3)] + P(\alpha_i/\alpha_i < 0)E(\beta_i M_3)\}$
$= \frac{1}{2}E(\alpha_i/\alpha_i > 0)$

- The expected payoff from passively investing in period 2 is given by :

$\{E(\alpha_i/\theta_{i1})+E(\beta_i M_2/\theta_{i1})\}$
$+ \{P(\alpha_i/\alpha_i>0)[E(\alpha_i)+E(\beta_i M_3)]+P(\alpha_i/\alpha_i<0)E(\beta_i M_3)\}$
$= 0$
Hence she always actively trades.

Period 1

In this paragraph I solve for the optimal decision of investor i whether or not to actively trade in period 1. I show that she always actively trades in period 1 in order to seize the option value of learning about her α_i.

The intuition goes as follows. Individual i takes her decision at the beginning of period 1 by comparing the expected payoffs of actively trading versus passively investing over the 3 periods. Suppose that individual i has a negative α_i. If she passively invests in period 1, we know that she will trade in period 2 (from the above paragraph) and that she will refrain from trading in period 3, when uncertainty is resolved. Hence she will have been hurt by actively trading with a negative α_i in 1 period only. On the contrary, if she decides to actively invest in period 1, she will refrain from trading in period 2 as she observes poor portfolio performance and in period 3 when uncertainty is resolved. Hence she will have been hurt by actively trading with a negative α_i in one period only.

Now suppose that individual i has a positive α_i. The same reasoning shows that by passively investing in period 1 she makes money by actively trading in 2 out of 3 periods only. However, if she actively trades in period 1, she makes money by actively trading in 3 out of 3 periods.

Hence, active trading provides limited downside and a clear upside to individual i. Thus she always decides to actively trade rather than passively invest in period 1.

In other words,

- The expected payoff from actively trading in period 1 is given by :

$E(\alpha_i) + E(\beta_i M_1)$
$+P(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0)\,\{E(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0) + E(\beta_i M_2/E(\alpha_i/R_{i1}, M_1) > 0)\} + P(\alpha_i/E(\alpha_i/R_{i1}, M_1) \leq 0)E(\beta_i M_2/E(\alpha_i/R_{i1}, M_1) \leq 0)$
$+\frac{1}{2}E(\alpha_i/\alpha_i > 0)$
$= P(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0)E(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0) + \frac{1}{2}E(\alpha_i/\alpha_i > 0)$

- The expected payoff from passively investing in period 1 is given by :

$E(\alpha_i) + E(\beta_i M_1)$
$+P(\alpha_i/E(\alpha/R_{i1}, M_1) > 0)\,\{E(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0) + E(\beta_i M_2/E(\alpha_i/R_{i1}, M_1) > 0)\} + P(\alpha_i/E(\alpha_i/R_{i1}, M_1) \leq 0)E(\beta_i M_2/E(\alpha_i/R_{i1}, M_1) \leq 0)$
$+\frac{1}{2}E(\alpha_i/\alpha_i > 0)$
$= \frac{1}{2}E(\alpha_i/\alpha_i > 0)$
Hence individual i actively trades in period 1 if:
$P(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0)E(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0) > 0$

Let us first show that $P(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0)$ is strictly positive. Since it is positive, it is sufficient to show that it is not equal to zero. Note that

$E(\alpha_i/E(\alpha_i/R_{i1}, M_1)) = 0$. Since $E(\alpha/R_{i1}, M_1)$ takes positive and negative values (it is not always zero), we need to have $P(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0) > 0$.

Let us now show that $E(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0) > 0$. Let us rewrite:

$E(\alpha_i/E(\alpha_i/R_{i1}, M_1) > 0) = E(\alpha_i 1_{E(\alpha_i/R_{i1},M_1)>0}) = E(E(\alpha_i 1_{E(\alpha_i/R_{i1},M_1)>0}/R_{i1}, M_1)) = E(1_{E(\alpha_i/R_{i1},M_1)>0} \times E(\alpha_i/R_{i1}, M_1))$

This last expression is strictly positive. It can be shown indeed that $E(f \times 1_{f>0}) > 0$ unless f is everywhere negative.

To see this, suppose$f$ is not everywhere negative. $\{f > 0\} = \bigcup_n \{f > \frac{1}{n}\}$.

Now note that $\exists n$ such that $E(\{f \times 1_{\{f>0\}}\}) > \frac{1}{n} P(\{f > \frac{1}{n}\}) > 0$.

Hence $P(\alpha_i / E(\alpha_i / R_{i1}, M_1) > 0) E(\alpha_i / E(\alpha_i / R_{i1}, M_1) > 0)$¿0 and individual i always actively trades in period 1.

Prediction 1

In period 2, individual i has observed the market return, m_1, and her portfolio return, r_{i1}. Individual i actively trades in period 2 if the expectation of his α_i conditional on his information set is positive, that is if (according to the projection theorem for normal variables):

$E(\alpha_i / Z_{i1} = r_{i1}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}(r_{i1} - m_1) > 0$, where $Z_{i1} = \alpha_i + \beta_i m_1$

Taking this expression conditional on $r_{i,1} > 0$ gives:

$E(\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}(\alpha_i + (\beta_i - 1) m_1) / \alpha_i + \beta m_1 > 0) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} E(\alpha_i + \beta m_1 / \alpha_i + \beta m_1 > 0) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} \sqrt{\frac{2}{\pi}} \sqrt{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}$

Taking this expression conditional on $r_{i,1} < 0$ gives:

$E(\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}(\alpha_i + (\beta_i - 1) m_1) / \alpha_i + \beta m_1 < 0) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} E(\alpha_i + \beta m_1 / \alpha_i + \beta m_1 < 0) = -\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} \sqrt{\frac{2}{\pi}} \sqrt{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}$

Hence the result

Prediction 2

In period 2, individual i has observed the market return, m_1, and her portfolio return, r_{i1}. Individual i actively trades in period 2 if the expectation of his α_i conditional on his information set is positive, that is if:

$E(\alpha_i / Z_{i1} = r_{i1}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}(r_{i1} - m_1) > 0$, where $Z_{i1} = \alpha_i + \beta_i m_1$

Taking this expression conditional on $\alpha_i > 0$ gives:

$E(\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}(\alpha_i + (\beta_i - 1) m_1) / \alpha_i > 0) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} E(\alpha_i / \alpha_i > 0) = \frac{\sigma_\alpha^3}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} \sqrt{\frac{2}{\pi}}$

Taking this expression conditional on $\alpha_i > 0$ gives:

$E(\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}(\alpha_i + (\beta_i - 1) m_1) / \alpha_i \leq 0) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} E(\alpha_i / \alpha_i \leq 0) = -\frac{\sigma_\alpha^3}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} \sqrt{\frac{2}{\pi}}$

Hence the result.

Prediction 3

In period 2, individual i has observed the market return, m_1, and her portfolio return, r_{i1}. Individual i actively trades in period 2 if the expectation of his α_i conditional on his information set is positive, that is if:

$E(\alpha_i / Z_{i1} = r_{i1}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}(r_{i1} - m_1) > 0$, where $Z_{i1} = \alpha_i + \beta_i m_1$

Taking this expression conditional on $\beta_i > 1$ gives:

$E(\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}(\alpha_i + (\beta_i - 1) m_1) / \beta_i > 1) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} E(m_1 (\beta_i - 1) / \beta_i > 1) = \frac{\sigma_\alpha^2 m_1}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} \sigma_\beta \sqrt{\frac{2}{\pi}}$

Taking this expression conditional on $\beta_i \leq 1$ gives:

$E(\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2}(\alpha_i + (\beta_i - 1) m_1) / \beta_i > 1) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} E(m_1 (\beta_i - 1) / \beta_i > 1) = \frac{\sigma_\alpha^2 m_1}{\sigma_\alpha^2 + m_1^2 \sigma_\beta^2} (-\sigma_\beta \sqrt{\frac{2}{\pi}})$

Hence the result.

Tables and Figures

Figure 1: Model Time line

This figure displays the time line of the model. At the beginning of each period, the arrow going up means that individual chooses to actively trade in period t and get $\alpha_i + \beta_i \times M_t$ where M_t is the market return. The flat arrow means that individual chooses to passively invest in period t and get $\beta_i \times M_t$. Information set at each node is briefly described inside boxes. The dotted line shows the path individuals never take.

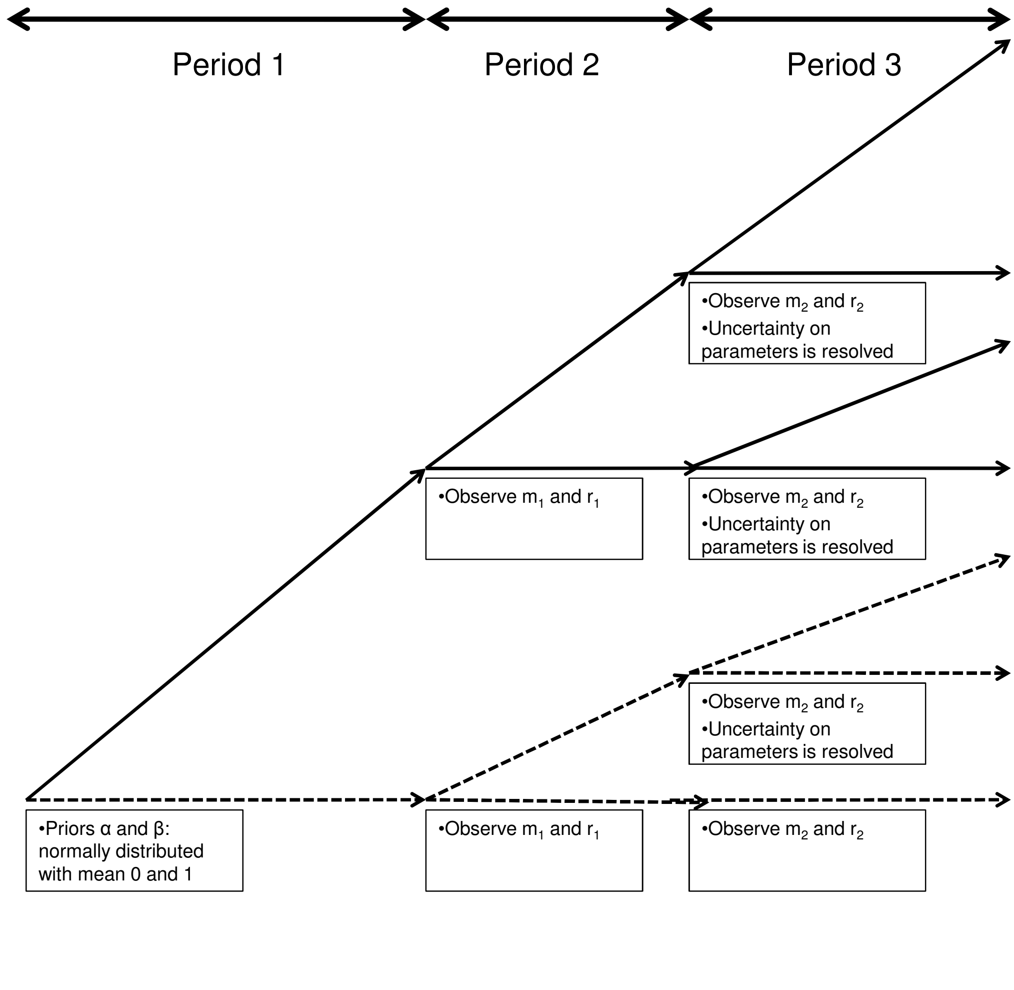

Figure 2: Average Period 2 Conditional Expectation of α_i by Period 1 Performance

This figure displays the value of $E(\alpha_i/\theta_{i1})$, the expectation of α_i at the beginning of period 2, conditional on portfolio returns and market returns observed in period 1. $E(\alpha_i/\theta_{i1})$ is a function of period 1 market return. As derived in section 5, individual i will actively trade in period 2 if $E(\alpha_i/\theta_{i1}) > 0$ and passively invest otherwise. The black line in the figure below is the average value of $E(\alpha_i/\theta_{i1})$ across individuals who obtained positive performance in period 1, that is $r_{i1} > 0$; the grey line is the average value of $E(\alpha_i/\theta_{i1})$ across individuals who obtained negative performance in period 1, that is $r_{i1} \leq 0$. On average, individual investors who obtained positive performance in period 1 will actively trade in period 2 while individual investors who obtained negative performance in period 1 won't. I use some arbitrary values of σ_α and σ_β that I obtain from the dataset used in this paper.

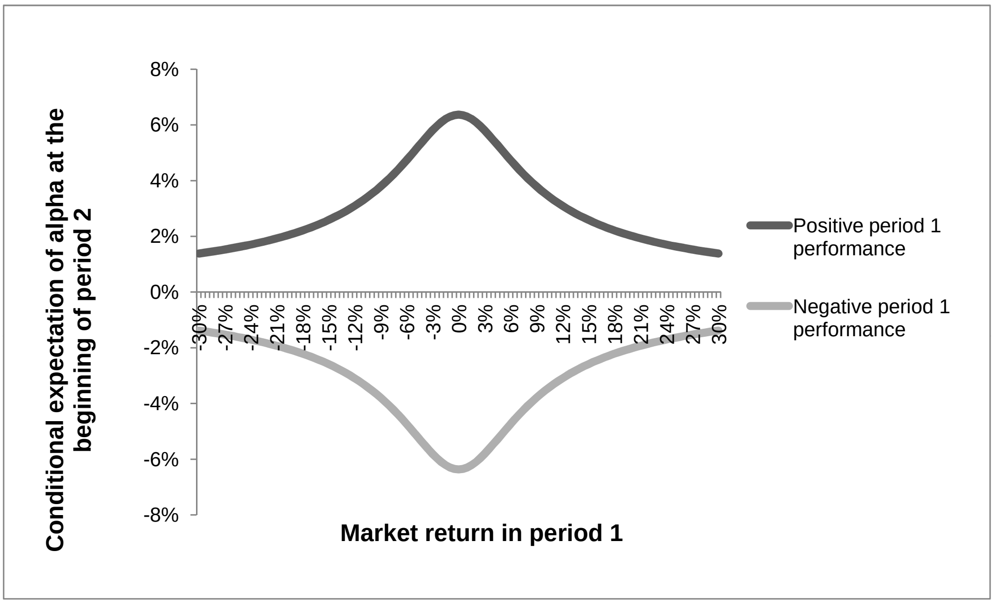

Figure 3: Average Period 2 Conditional Expectation of α_i by Alpha

This figure displays the value of $E(\alpha_i/\theta_{i1})$, the expectation of α_i at the beginning of period 2, conditional on portfolio returns and market returns observed in period 1. $E(\alpha_i/\theta_{i1})$ is a function of period 1 market return. As derived in section 5, individual i will actively trade in period 2 if $E(\alpha_i/\theta_{i1}) > 0$ and passively invest otherwise. The black line in the figure below is the average value of $E(\alpha_i/\theta_{i1})$ across individuals with $\alpha_i > 0$; the grey line is the average value of $E(\alpha_i/\theta_{i1})$ across individuals with $\alpha_i \leq 0$. On average, high alpha individuals choose to actively trade in period 2. I use some arbitrary values of σ_α and σ_β that I obtain from the dataset used in this paper..

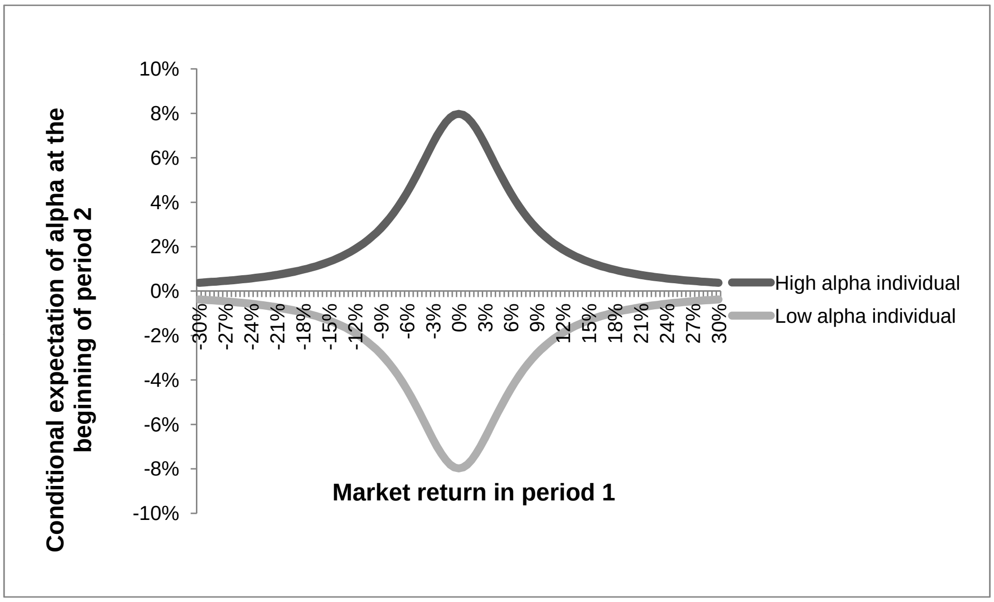

Figure 4: Average Period 2 Conditional Expectation of α_i by Market Exposure
This figure displays the value of $E(\alpha_i/\theta_{i1})$, the expectation of α_i at the beginning of period2, conditional on portfolio returns and market returns observed in period 1. $E(\alpha_i/\theta_{i1})$ is a function of period 1 market return. As derived in section 5, individual i will actively trade in period 2 if $E(\alpha_i/\theta_{i1}) > 0$ and passively invest otherwise. The black line in the figure below is the average value of $E(\alpha_i/\theta_{i1})$ across individuals with $\beta_i > 1$; the grey line is the average value of $E(\alpha_i/\theta_{i1})$ across individuals with $\beta_i \leq 1$. On average, high beta individuals actively trade in period 2 when period 1 market returns have been positive. I use some arbitrary values of σ_α and σ_β that I obtain from the dataset used in this paper.

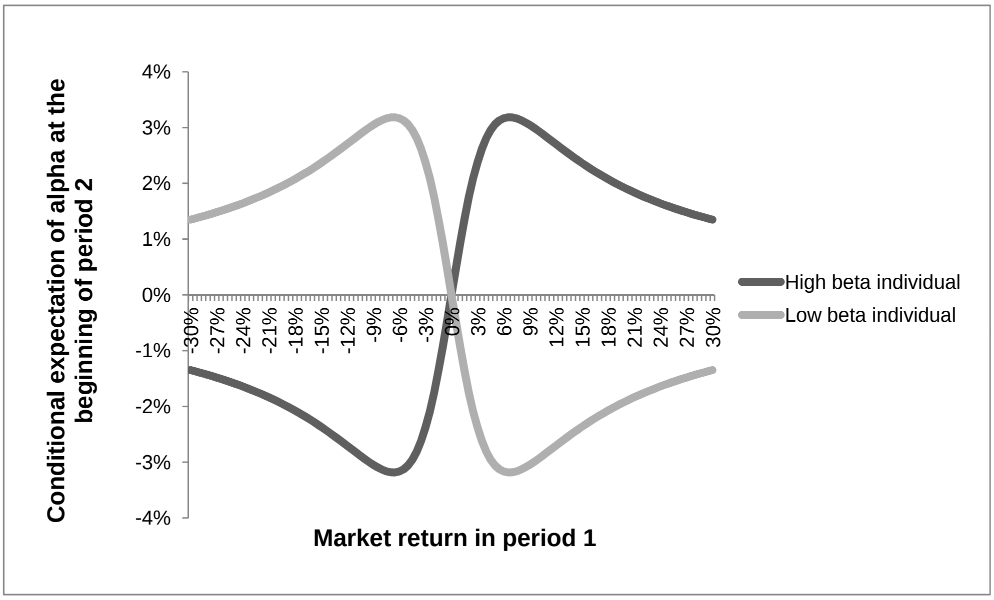

Figure 5: Answers to Mifid Questionnaire by SRD versus NO SRD Investors
This figure presents the average answer by 833 individuals in the dataset either using the SRD service or not using it to the question "What are your main investment objectives?".

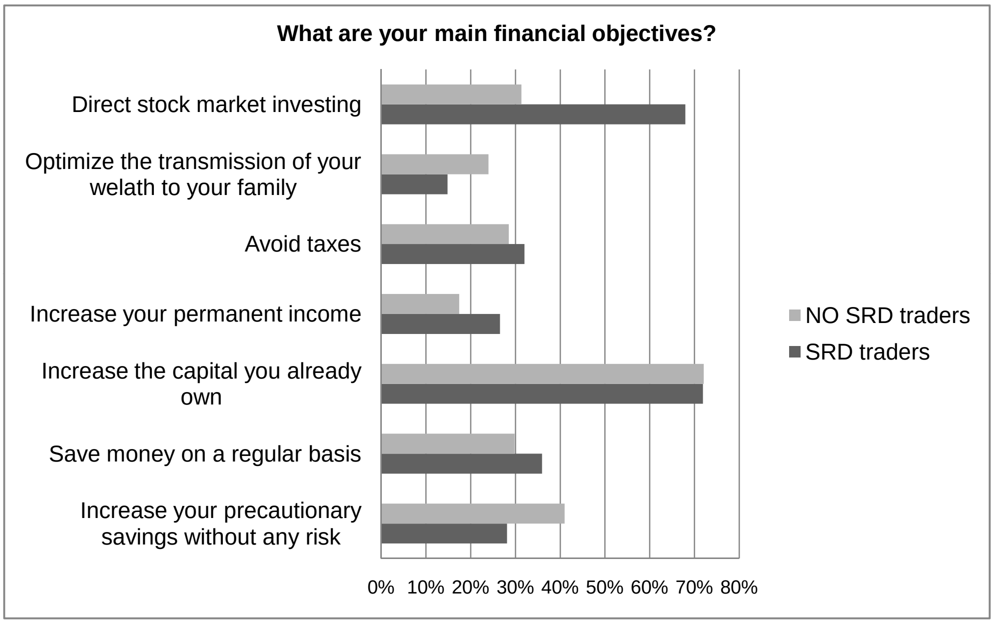

Figure 6: Experience and the Sensitivity of Active Trading to past Performance

These two figures plot the confidence interval of the coefficients of the following series of regressions which are run in the cross-section of actively trading investors at each experience month e:

$$T_{i,e+1} = \lambda \alpha_{i,e} + \epsilon_{i,e}$$

$$T_{i,e+1} = \lambda \gamma_{i,e} + \epsilon_{i,e}$$

where $T_{i,e+1}$ is a dummy equals to one if individual i is active in month $e+1$ or zero if individual i stopped trading. $\alpha_{i,e}$ is the alpha of investor i in experience month e and $\gamma_{i,e} = \pi_{i,e} - \alpha_{i,e}$ is the aggregate factor exposure performance over all three risk factors of individual i in experience month e.

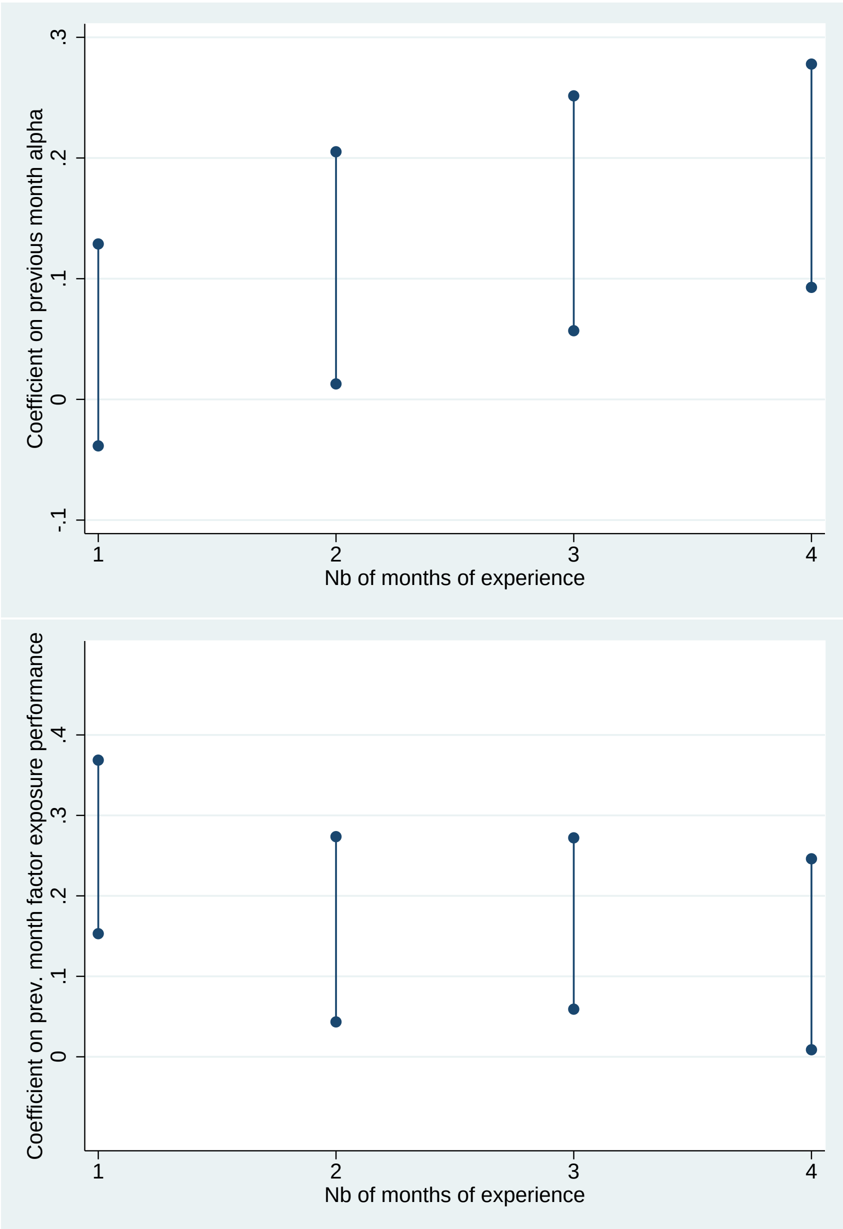

Table 1: Summary Statistics

This table presents summary statistics for the sample of active traders used in this paper.

	Obs.	Mean	Std. dev.
Individual investors characteristics			
Number of active trading months	14151	7.73	13.82
Number of different stocks traded	14151	12.46	16.38
Trading measures (monthly)			
Log number of trades	109394	1.83	1.25
Log eur volume traded	109394	9.98	1.75
Log average volume per stock traded	109394	7.88	1.49
Eur signed volume over eur volume	109394	0.08	0.56
Log average size of trades	109394	8.15	0.98
Continuation dummy	109394	0.91	0.29
Unweighted performance measures (monthly)			
Performance	109394	-0.001	0.083
Residual performance (Alpha)	109394	-0.001	0.071
Mkt exposure performance, $\beta\pi_{i,t}^{Mkt}$	109394	-0.001	0.065
SMB exposure performance, $\beta\pi_{i,t}^{SMB}$	109394	0.002	0.025
HML exposure performance, $\beta\pi_{i,t}^{HML}$	109394	0.000	0.020
Mkt exposure, $\beta_{i,t}^{Mkt}$	109394	1.590	0.889
SMB exposure, $\beta_{i,t}^{SMB}$	109394	0.468	0.831
HML exposure, $\beta_{i,t}^{HML}$	109394	0.097	0.563
Mkt performance, $\pi_{i,t}^{Mkt}$	109394	0.001	0.029
SMB performance, $\pi_{i,t}^{SMB}$	109394	0.003	0.023
HML performance, $\pi_{i,t}^{HML}$	109394	0.004	0.031
Weighted performance measures (monthly)			
Performance	109394	-0.002	0.095
Residual performance (Alpha)	109394	-0.001	0.083
Mkt exposure performance, $\beta\pi_{i,t}^{Mkt}$	109394	-0.002	0.074
SMB exposure performance, $\beta\pi_{i,t}^{SMB}$	109394	0.001	0.028
HML exposure performance, $\beta\pi_{i,t}^{HML}$	109394	0.000	0.023
Mkt exposure, $\beta_{i,t}^{Mkt}$	109394	1.223	1.224
SMB exposure, $\beta_{i,t}^{SMB}$	109394	0.354	0.892
HML exposure, $\beta_{i,t}^{HML}$	109394	0.068	0.565
Mkt performance, $\pi_{i,t}^{Mkt}$	109394	0.000	0.032
SMB performance, $\pi_{i,t}^{SMB}$	109394	0.002	0.025
HML performance, $\pi_{i,t}^{HML}$	109394	0.003	0.034

Table 2: Sensitivity of Individual Investors Active Trading to Past Performance

This table presents the result of the following regression in the panel of 14151 distinct individual investors actively trading in 7.7 successive periods on average.

$$T_{i,t+1} = \lambda_1 \pi_{i,t} + \lambda_2 P_{i,t} + \kappa_i + \delta_e + \mu_t + \epsilon_{i,t}$$

where $T_{i,t+1}$ is a measure of trading activity of individual i in month $t+1$. I consider successively the log of the number of orders (column 1), the log of the eur volume traded (column 2), the log euro volume per stock traded (column 3), the excess volume purchased over volume sold normalized by total volume (column 4), the log of the average order size (column 5), and a dummy equals to one if individual i is active in month $t+1$ or if individual i stops trading (column 6). $\pi_{i,t}$ is the performance of individual i in month t as computed in section 2, $P_{i,t}$ is the increase in the log eur value of individual i's portfolio in month t and κ_i, δ_e and μ_t are respectively individual, experience (the number of trading month since individual i started active trading) and time fixed effects. Standard errors are in parenthesis and are clustered at the monthly level. In Panel B, the same regression is run with the weighted performance of individual i in month t where the performance on each stock traded by individual i in month t is weighted by the ratio of the euro volume traded of stock s in month t to the total euro volume traded in month t.

	(1)	(2)	(3)	(4)	(5)	(6)
	PANEL A: unweighted measure of performance					
Prev. month perf.	0.569***	0.898***	0.270***	0.408***	0.328***	0.086***
	(0.083)	(0.111)	(0.048)	(0.062)	(0.037)	(0.018)
Log portfolio value	-0.001	-0.002*	-0.001	0.002**	-0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	1.492***	9.573***	8.285***	0.084***	8.080***	0.742***
	(0.049)	(0.056)	(0.046)	(0.028)	(0.023)	(0.018)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Experience FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,394	109,394	109,394	109,394	109,394	109,394
R-squared	0.551	0.666	0.692	0.283	0.776	0.469
	PANEL B: weighted measure of performance					
Prev. month perf.	0.304***	0.469***	0.103***	0.279***	0.165***	0.059***
	(0.070)	(0.089)	(0.036)	(0.055)	(0.031)	(0.014)
Log portfolio value	-0.001	-0.003*	-0.001	0.002**	-0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	1.485***	9.561***	8.281***	0.080***	8.076***	0.742***
	(0.049)	(0.057)	(0.046)	(0.028)	(0.023)	(0.018)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Experience FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,394	109,394	109,394	109,394	109,394	109,394
R-squared	0.550	0.665	0.692	0.282	0.776	0.469

Table 3: Sensitivity of Households Active Trading to their Ability and Market Exposure
This table presents the result of the following regression in the panel of 14151 distinct individual investors actively trading in 7.7 successive periods on average.

$$T_{i,t+1} = \lambda_1 \alpha_{i,t} + \lambda_2 \beta\pi^{Mkt}_{i,t} + \lambda_3 \beta\pi^{SMB}_{i,t} + \lambda_4 \beta\pi^{HML}_{i,t}$$
$$+ \lambda_5 \pi^{Mkt}_{i,t} + \lambda_6 \pi^{SMB}_{i,t} + \lambda_7 \pi^{HML}_{i,t} + \lambda_8 \beta^{Mkt}_{i,t} + \lambda_9 \beta^{SMB}_{i,t} + \lambda_{10} \beta^{HML}_{i,t} + \lambda_{11} P_{i,t} + \kappa_i + \delta_e + \mu_t + \epsilon_{i,t}$$

where $T_{i,t+1}$ is a measure of trading activity of individual i in month $t+1$ .I consider successively the log of the number of orders (column 1), the log of the eur volume traded (column 2), the log euro volume per stock traded (column 3), the excess volume purchased over volume sold normalized by total volume (column 4), the log of the average order size (column 5), and a dummy equals to one if individual i is active in month $t+1$ or if individual i stops trading (column 6). $\beta\pi^{Mkt}_{i,t}$, $\beta\pi^{SMB}_{i,t}$and $\beta\pi^{HML}_{i,t}$ are the returns obtained from the exposure of individual i's trades to the three risk factors. The third component of the regression includes the following controls. $\pi^{Mkt}_{i,t}$, $\pi^{SMB}_{i,t}$and $\pi^{HML}_{i,t}$ are the returns on the indices replicating the risk factors. $\beta^{Mkt}_{i,t}$ $\beta^{SMB}_{i,t}$and $\beta^{HML}_{i,t}$ are the average exposure of the stocks traded by individual i to each of the three risk factors. $P_{i,t}$ is the increase in the log eur value of individual i's portfolio in month t and κ_i, δ_e and μ_t are respectively individual, experience (the number of trading month since individual i started active trading) and time fixed effects. Standard errors are in parenthesis and are clustered at the monthly level. In Panel B, the same regression is then run with variables weighted by the ratio of the euro volume traded of stock s in month t to the total euro volume traded in month t.

	(1)	(2)	(3)	(4)	(5)	(6)
	PANEL A: unweighted measure of performance					
Residual performance, $\alpha_{i,t}$	0.612***	0.972***	0.250***	0.424***	0.359***	0.086***
	(0.093)	(0.124)	(0.055)	(0.065)	(0.045)	(0.023)
Mkt exposure performance, $\beta\pi^{Mkt}_{i,t}$	0.841***	1.336***	0.514***	0.432***	0.495***	0.130***
	(0.155)	(0.188)	(0.108)	(0.122)	(0.069)	(0.033)
SMB exposure performance, $\beta\pi^{SMB}_{i,t}$	0.702***	1.206***	0.573***	0.492***	0.504***	0.170***
	(0.253)	(0.325)	(0.183)	(0.137)	(0.122)	(0.049)
HML exposure performance, $\beta\pi^{HML}_{i,t}$	0.814***	1.057***	-0.163	0.777***	0.243**	0.113**
	(0.247)	(0.300)	(0.176)	(0.186)	(0.095)	(0.045)
Mkt exposure, $\beta^{Mkt}_{i,t}$	0.008	0.006	0.015*	-0.004	-0.002	-0.003
	(0.008)	(0.011)	(0.008)	(0.005)	(0.005)	(0.002)
SMB exposure, $\beta^{SMB}_{i,t}$	-0.001	-0.016	-0.034***	0.005	-0.015***	0.002
	(0.009)	(0.014)	(0.008)	(0.005)	(0.006)	(0.002)
HML exposure, $\beta^{HML}_{i,t}$	0.014	0.018	-0.002	-0.008	0.004	0.003
	(0.010)	(0.014)	(0.010)	(0.006)	(0.005)	(0.002)
Mkt performance, $\pi^{Mkt}_{i,t}$	-0.978**	-1.552***	-0.436	-0.209	-0.574***	-0.095
	(0.471)	(0.592)	(0.296)	(0.352)	(0.181)	(0.066)
SMB performance, $\pi^{SMB}_{i,t}$	-0.663	-0.901	-0.016	-0.399	-0.238	-0.065
	(0.547)	(0.667)	(0.300)	(0.348)	(0.183)	(0.060)
HML performance, $\pi^{HML}_{i,t}$	0.112	0.121	-0.090	-0.231	0.010	-0.025
	(0.281)	(0.369)	(0.191)	(0.300)	(0.118)	(0.035)
Log portfolio value	-0.001	-0.002	-0.001	0.002**	-0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	1.476***	9.567***	8.287***	0.078***	8.090***	0.743***
	(0.053)	(0.061)	(0.047)	(0.028)	(0.024)	(0.018)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Experience FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,394	109,394	109,394	109,394	109,394	109,394
R-squared	0.551	0.666	0.692	0.283	0.776	0.470

	(1)	(2)	(3)	(4)	(5)	(6)
	PANEL B: weighted measure of performance					
Residual performance , $\alpha_{i,t}$	0.303***	0.453***	0.045	0.306***	0.150***	0.050***
	(0.067)	(0.091)	(0.046)	(0.056)	(0.040)	(0.019)
Mkt exposure performance, $\beta\pi_{i,t}^{Mkt}$	0.216	0.395*	0.092	0.280**	0.179***	0.073**
	(0.159)	(0.204)	(0.082)	(0.108)	(0.061)	(0.036)
SMB exposure performance, $\beta\pi_{i,t}^{SMB}$	0.410	0.736**	0.332**	0.462***	0.326***	0.143***
	(0.255)	(0.327)	(0.135)	(0.124)	(0.113)	(0.047)
HML exposure performance, $\beta\pi_{i,t}^{HML}$	0.823***	0.992***	-0.185	0.612***	0.169**	0.113***
	(0.235)	(0.289)	(0.138)	(0.179)	(0.084)	(0.043)
Mkt exposure, $\beta_{i,t}^{Mkt}$	-0.132***	-0.169***	-0.035***	-0.011***	-0.037***	-0.010***
	(0.013)	(0.015)	(0.005)	(0.004)	(0.004)	(0.001)
SMB exposure, $\beta_{i,t}^{SMB}$	0.067***	0.073***	-0.004	0.009*	0.006	0.005***
	(0.013)	(0.016)	(0.005)	(0.005)	(0.005)	(0.002)
HML exposure, $\beta_{i,t}^{HML}$	-0.000	0.003	-0.006	-0.006	0.004	0.003
	(0.017)	(0.021)	(0.006)	(0.006)	(0.006)	(0.002)
Mkt performance, $\pi_{i,t}^{Mkt}$	-0.672	-0.891	0.054	-0.149	-0.219	-0.043
	(0.495)	(0.601)	(0.230)	(0.295)	(0.141)	(0.060)
SMB performance, $\pi_{i,t}^{SMB}$	-1.022*	-1.250**	-0.022	-0.228	-0.228	-0.071
	(0.528)	(0.630)	(0.226)	(0.287)	(0.145)	(0.051)
HML performance, $\pi_{i,t}^{HML}$	0.209	0.209	0.016	-0.263	0.000	-0.006
	(0.264)	(0.327)	(0.129)	(0.242)	(0.090)	(0.027)
Log portfolio value	-0.001	-0.003*	-0.001	0.002**	-0.002**	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	1.583***	9.693***	8.320***	0.085***	8.110***	0.749***
	(0.055)	(0.061)	(0.046)	(0.028)	(0.023)	(0.018)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Experience FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,394	109,394	109,394	109,394	109,394	109,394
R-squared	0.556	0.670	0.692	0.283	0.777	0.470

Table 4: Auto-correlation of Risk Factor Returns

This table the presents the auto-correlation of the three risk factors monthly returns.

	R_t^{Mkt}	R_t^{SMB}	R_t^{HML}
Auto-correlation coefficient	-0.104	0.001	0.166*
P-value	0.2534	0.988	0.068
Nb of observations	122	122	122

Table 5: Co-movement of Risk Factors and Individual Investors Risk Factor Exposure

I run the following regression for each factor $f \in \{Mkt, SMB, HML\}$:

$$R_t^f = \lambda_1 \beta_{i,t}^f + \kappa_i + \delta_e + \epsilon_{i,t}$$

where R_t^f is the return of risk factor f in month t. κ_i, δ_e and μ_t are respectively individual, experience (the number of trading month since individual i started active trading) and time fixed effects. Standard errors are in parenthesis and are clustered at the monthly level.

	R_t^{Mkt}	R_t^{SMB}	R_t^{HML}
Mkt exposure, $\beta_{i,t}^{Mkt}$	-0.958***		
	(0.343)		
SMB exposure, $\beta_{i,t}^{SMB}$		0.0262	
		(0.273)	
HML exposure, $\beta_{i,t}^{HML}$			0.251
			(0.473)
Constant	1.704**	-0.760*	-5.684***
	(0.790)	(0.420)	(0.690)
Individual FE	Yes	Yes	Yes
Experience FE	Yes	Yes	Yes
Observations	109,394	109,394	109,394
R-squared	0.141	0.126	0.259

Table 6: Persistence in Ability and Factor Exposure over Time

I run the following regression for each factor $f \in \{Mkt, SMB, HML\}$:

$$\beta^f_{i,t+1} = \lambda_1 \beta^f_{i,t} + \delta_e + \mu_t + \epsilon_{i,t}$$

where $\beta^f_{i,t+1}$ is the exposure of individual i to factor f in month t. $ta_e$and μ_t are respectively experience (the number of trading month since individual i started active trading) and time fixed effects. Standard errors are in parenthesis and are clustered at the monthly level.

	$\alpha_{i,t+1}$	$\beta^{Mkt}_{i,t+1}$	$\beta^{SMB}_{i,t+1}$	$\beta^{HML}_{i,t+1}$
Residual performance, $\alpha_{i,t}$	0.0139			
	(0.009)			
Mkt exposure, $\beta^{Mkt}_{i,t}$		0.133***		
		(0.019)		
SMB exposure, $\beta^{SMB}_{i,t}$			0.106***	
			(0.022)	
HML exposure, $\beta^{HML}_{i,t}$				0.0680***
				(0.018)
Constant	0.0155***	1.310***	0.835***	0.183***
	(0.000)	(0.017)	(0.009)	(0.004)
Month FE	Yes	Yes	Yes	Yes
Experience FE	Yes	Yes	Yes	Yes
Observations	100,632	100,632	100,632	100,632
R-squared	0.082	0.244	0.181	0.257

Table 7: Sensitivity of Active Trading to Performance interacted with Absolute Factor Returns

This table presents the result of the following regression in the panel of 14151 distinct individual investors.

$$T_{i,t+1} = \lambda_1 \pi_{i,t} + \lambda_2 AbsR_t^{Mkt} \times \pi_{i,t} + \lambda_3 AbsR_t^{SMB} \times \pi_{i,t} + \lambda_4 AbsR_t^{HML} \times \pi_{i,t}$$
$$+\lambda_5 AbsR_t^{Mkt} + \lambda_6 AbsR_t^{SMB} + \lambda_7 AbsR_t^{HML} + \lambda_8 P_{i,t} + \kappa_i + \delta_e + \epsilon_{i,t}$$

where $T_{i,t+1}$ is a measure of trading activity of individual i in month $t+1$. I consider successively the log of the number of orders (column 1), the log of the eur volume traded (column 2), the log euro volume per stock traded (column 3), the excess volume purchased over volume sold normalized by total volume (column 4), the log of the average order size (column 5), and a dummy equals to one if individual i is active in month $t+1$ or if individual i stops trading (column 6). $\pi_{i,t}$ is the performance of individual i in month t as computed in section 2, $AbsR_t^f$ is the absolute value of the return of risk factor f in month t, $P_{i,t}$ is the increase in the log eur value of individual i's portfolio in month t, and κ_i and δ_e are respectively individual and experience fixed effects . Standard errors are in parenthesis and are clustered at the monthly level. In Panel B, the same regression is run with the weighted performance of individual i in month t where the performance on each stock traded by individual i in month t is weighted by the ratio of the euro volume traded of stock s in month t to the total euro volume traded in month t.

	(1)	(2)	(3)	(4)	(5)	(6)
	PANEL A: unweighted measure of performance					
Previous month performance, $\pi_{i,t}$	1.457***	2.099***	0.246	1.001***	0.642***	0.115**
	(0.240)	(0.302)	(0.152)	(0.192)	(0.125)	(0.056)
$AbsR_t^{Mkt} \times \pi_{i,t}$	-5.047***	-5.204**	1.186	-2.990**	-0.157	-0.215
	(1.836)	(2.251)	(1.066)	(1.361)	(0.889)	(0.287)
$AbsR_t^{SMB} \times \pi_{i,t}$	-9.168***	-10.241***	2.224	-4.537	-1.073	-0.500
	(2.962)	(3.752)	(1.938)	(2.975)	(1.594)	(0.530)
$AbsR_t^{HML} \times \pi_{i,t}$	-0.042	-2.838	-2.456*	0.224	-2.796***	0.476
	(1.801)	(2.123)	(1.402)	(1.588)	(1.046)	(0.357)
$AbsR_t^{Mkt}$	0.412	-0.597	-0.494*	-0.136	-1.009***	-0.008
	(0.471)	(0.598)	(0.256)	(0.263)	(0.283)	(0.097)
$AbsR_t^{SMB}$	1.568**	1.448*	-0.429	0.056	-0.120	0.221**
	(0.643)	(0.776)	(0.348)	(0.314)	(0.295)	(0.105)
$AbsR_t^{HML}$	-0.009	-0.262	-0.342	-0.043	-0.253	0.022
	(0.455)	(0.546)	(0.219)	(0.219)	(0.227)	(0.065)
Log portfolio value	-0.001	-0.002	-0.001	0.002**	-0.001*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	1.423***	9.669***	8.518***	0.065***	8.246***	0.583***
	(0.048)	(0.054)	(0.038)	(0.023)	(0.019)	(0.018)
Individual and Experience FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,394	109,394	109,394	109,394	109,394	109,394
R-squared	0.535	0.653	0.689	0.261	0.767	0.455

	(1)	(2)	(3)	(4)	(5)	(6)
		PANEL B: weighted measure of performance				
Previous month performance, $\pi_{i,t}$	1.101***	1.706***	0.386***	0.783***	0.605***	0.108***
	(0.166)	(0.180)	(0.112)	(0.100)	(0.081)	(0.032)
$AbsR_t^{Mkt} \times \pi_{i,t}$	-1.688	-1.896	0.447	-1.763**	-0.208	-0.065
	(1.060)	(1.283)	(0.686)	(0.733)	(0.609)	(0.173)
$AbsR_t^{SMB} \times \pi_{i,t}$	-6.207***	-7.528***	-0.509	-2.373	-1.322	-0.508
	(2.250)	(2.433)	(1.511)	(1.843)	(1.041)	(0.345)
$AbsR_t^{HML} \times \pi_{i,t}$	-0.547	-2.441	-2.122*	1.029	-1.895**	0.382
	(1.498)	(1.752)	(1.135)	(1.313)	(0.861)	(0.256)
$AbsR_t^{Mkt}$	0.538	-0.473	-0.526**	-0.086	-1.012***	-0.003
	(0.464)	(0.577)	(0.254)	(0.246)	(0.276)	(0.095)
$AbsR_t^{SMB}$	1.550**	1.425*	-0.417	0.039	-0.126	0.221**
	(0.665)	(0.795)	(0.348)	(0.313)	(0.296)	(0.104)
$AbsR_t^{HML}$	-0.035	-0.291	-0.340	-0.049	-0.256	0.022
	(0.460)	(0.546)	(0.223)	(0.217)	(0.230)	(0.065)
Log portfolio value	-0.000	-0.002	-0.001	0.002**	-0.001*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Constant	1.419***	9.665***	8.520***	0.062***	8.246***	0.583***
	(0.048)	(0.055)	(0.038)	(0.023)	(0.020)	(0.018)
Individual and Experience FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	109,394	109,394	109,394	109,394	109,394	109,394
R-squared	0.535	0.653	0.689	0.261	0.767	0.455

Table 8: First Period Experience and the Speed of Exit

I run the following regression on the sample of investors for which I observed an exit before December 2010:

$S_i = \lambda_1 \alpha_{i,1} + \lambda_2 \gamma_{i,1}$

where S_i is the inverse of the number of successive active trading periods of individual i, $\gamma_{i,1} = \pi_{i,1} - \alpha_{i,1}$ is the aggregate factor exposure performance over all three risk factors of individual i in the first month she trades.Regressions are run for weighted and unweighted measures of performance respectively in columns 1 and 2. Standard errors are in parenthesis.

	Unweighted measures of perf.	Weighted measures of perf.
	Speed of exit, S_i	Speed of exit, S_i
Residual performance , $\alpha_{i,1}$	0.008	0.028
	(0.042)	(0.035)
Factor exposure performance, $\gamma_{i,1}$	-0.220***	-0.116***
	(0.053)	(0.045)
Constant	0.466***	0.467***
	(0.003)	(0.003)
Observations	13,754	13,754
R-squared	0.001	0.001