Journal of Economic Behavior & Organization 107 (2014) 487–511

Contents lists available at ScienceDirect

Journal of Economic Behavior & Organization

journal homepage: www.elsevier.com/locate/jebo

Technical analysis and individual investors[☆]

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ARTICLE INFO

Article history:
Received 31 January 2013
Received in revised form 24 February 2014
Accepted 1 April 2014
Available online 13 April 2014

JEL classification:
D03
G02
G11
G24

Keywords:
Behavioral finance
Household finance
Individual investors
Investor behavior
Investor performance
Technical analysis
Speculation

ABSTRACT

We find that individual investors who use technical analysis and trade options frequently make poor portfolio decisions, resulting in dramatically lower returns than other investors. The data on which this claim is based consists of transaction records and matched survey responses of a sample of Dutch discount brokerage clients for the period 2000–2006. Overall, our results indicate that individual investors who report using technical analysis are disproportionately prone to have speculation on short-term stock-market developments as their primary investment objective, hold more concentrated portfolios which they turn over at a higher rate, are less inclined to bet on reversals, choose risk exposures featuring a higher ratio of nonsystematic risk to total risk, engage in more options trading, and earn lower returns.

1. Introduction

The intersection between the literature on individual investors and the literature on technical analysis is sparse. As a result, knowledge about individual investors' use of technical analysis has been limited. In the present paper, we present the

☆ We thank a large online discount broker and its employees for making available the data used in this paper. We thank seminar participants at the University of Münster for valuable feedback on a previous draft of the paper. We thank the journal editor, William Neilson, and the special issue editors, Remco Zwinkels, Martijn van den Assem, and Doron Kliger, for constructive guidance through the review process and helpful feedback. We thank three anonymous reviewers for valuable comments to improve the paper. We thank Jeroen Derwall for technical assistance. Part of the work was completed while Arvid Hoffmann was visiting the Leavey School of Business at Santa Clara University, Aalto University School of Economics, and the Foster School of Business at University of Washington, whose hospitality is gratefully acknowledged. This paper draws on different versions of a working paper that we circulated previously under the titles "Discount Brokerage, Online Trading, and Data Overload: Increased Emphasis on Technical Analysis, Intuition, and Speculation" and "The High Cost of Technical Analysis and Speculation." We subsume these previous versions of the paper in the current version.
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http://dx.doi.org/10.1016/j.jebo.2014.04.002
0167-2681/

results of a new study which deepens our understanding about how using technical analysis impacts individual investors' portfolios.

The existing literature on technical analysis effectively ignores the experience of individual investors. Instead, it emphasizes its efficacy, the time periods in which its use is associated with abnormal trading profits, and the markets where such abnormal profits have been earned.[1] In a comment about individual investors that serves as an exception, Neely (1997) describes the profitable use of technical analysis to trade in foreign exchange markets, but states the following: "Technical trading is much less useful for individuals, who would face much higher transactions costs and must consider the opportunity cost of the time necessary to become an expert on foreign exchange speculating and to keep up with the market on a daily basis. . . In addition to higher transactions costs, individual investors following technical rules also must accept the risk that such a strategy entails." (p. 31). We note that Neely provides no empirical evidence to support his remarks about individual investors' use of technical analysis.

Most of what is known about the actual use of technical analysis by individual investors comes from a study of U.S. investors by Lewellen et al. (1980) (LLS),[2] and is based on transaction records and matched survey responses from the period 1964–1970. In line with Neely's remark, the findings from this study suggest that technical analysis severely degrades the performance of individual investors' portfolios. LLS report that investors who trade the most frequently use technical analysis to a disproportionate degree and underperform other investors by 4.1% per year on a risk-adjusted basis. This result is economically important: LLS find that 27% of the investors in their sample use technical analysis.

The LLS results about technical analysis being both costly to individual investors and widespread were economically important during the 1960s. But are these results robust in respect to time and space? This is a critical question, and forms the starting point of our investigation.

The existing literature on individual investor behavior since LLS has effectively ignored technical analysis. We believe this is because of a major difference in the type of data LLS used in their study and the data used in more recent studies by other authors. LLS combine their transaction data with matched survey data in which investors report the strategies they use (such as technical analysis), the investment objectives they maintain (such as achieving short-term capital gains), and other related information. In contrast, the data used by more recent studies, such as those by Odean (1998a, 1999) and Barber and Odean (2000, 2001a,b, 2002; Barber and Odean, 2008), only include account-level transactions, not survey information.[3]

In this paper, we report that the key findings from LLS (1980) are robust to time and space, and moreover are driven by investors' decisions about portfolio concentration, turnover, and options trading. Our study uses data from the Netherlands which cover the period 2000–2006 and are from a discount broker where investors trade online. These data consist of transaction records and matched survey responses, the same structure used by LLS.[4]

LLS apply the term "high roller" to describe high-turnover investors, and associate high rollers with the use of technical analysis as a strategy and achieving short-term capital gains as an objective. Notably, LLS make no effort to isolate the separate effects of technical analysis, a focus on achieving short-term capital gains, and high turnover. In contrast, we do, and believe that ours is the first paper to isolate the impact of individual investors' use of technical analysis on concentration, turnover, derivatives use, betting on reversals, risk-taking, and returns. Our new findings constitute the major contributions of the current paper.

We find that investors who report using technical analysis hold more concentrated portfolios than other investors, and have higher ratios of nonsystematic risk to total risk. They also trade more frequently than other investors, especially in respect to options. As a result of these behavior patterns, investors using technical analysis earn lower raw and risk-adjusted returns than other investors. The magnitudes are economically important: controlling for concentration and turnover, the marginal cost associated with technical analysis is approximately 50 basis points of raw return per month. Turnover associated with technical analysis adds a further 20 basis points per month of cost. Concentration adds an additional 2 basis points.

A major finding from our study concerns investors who both trade options frequently and use technical analysis. For "high derivative rollers," the marginal cost of technical analysis from poor portfolio selection is 140 basis points, not the 50 basis points which we find for the full sample of investors, with turnover linked to technical analysis adding an additional 29 basis points of cost. Importantly, we find that outside the group of high derivative rollers, the average cost of using technical analysis is small and not statistically significant.

Our paper makes three contributions to the behavioral finance literature on individual investors. First, we find that the choices of investors in our data using technical analysis are consistent with the behavior of subjects in experimental studies who use price charts. Second, we find that the behavioral traits of investors using technical analysis are similar to those which the literature links to excessive optimism and overconfidence. Third, we find that high derivative rollers who use

[1] We discuss selections from this literature in Appendix A1.

[2] Throughout the paper, we use the abbreviation LLS when citing papers co-authored by Lease, Lewellen, and Schlarbaum. Note, however, that the actual order of authors varies across these citations.

[3] Both sets of data include individual account-level transaction data—LLS (1974, 1976, 1977, 1978a,b, 1980) from a full-fee brokerage, and Odean (1998a, 1999) and Barber and Odean (2000, 2001a,b, 2002, 2008) from a discount brokerage.

[4] In the body of the paper (Section 4.6), we discuss both similarities and differences in the two databases.

technical analysis and have speculation as their primary investment objective exhibit the same behavioral traits as investors who favor lottery stocks.

The paper is organized as follows. Section 2 describes the literature we use to develop hypotheses, which we set out in Section 3. Section 4 introduces our data and methods. Section 5 reports results. Section 6 discusses some broader issues. Section 7 concludes.

2. Literature: preferences, judgmental biases, and portfolio decisions

This section describes the behavioral literature upon which we base our hypotheses. We divide this literature into three groups, according to focus: (1) speculation[5] as an objective; (2) judgmental biases that stem from the use of technical analysis; and (3) the manner in which speculation as an objective and judgmental biases impact concentration, turnover, and the risk-return profile.

2.1. Speculation and portfolio decisions

On the theoretical front, Shefrin and Statman (2000) suggest that individual investors have dual needs for downside protection and upside potential, and aspirational goals as well. This theory implies that investors are prone to build portfolios that emphasize both safe bond-like securities and risky option- and lottery-like securities. The strength of the needs for upside potential and achieving aspiration relative to the need for downside protection determine the degree to which investors hold risky securities which are speculative.[6]

On the empirical front, Kumar (2009) describes individual investors' disproportionate holdings of stocks with lottery-like features. Han and Kumar (2013) report that these lottery-like stocks are overpriced on average. Dorn and Sengmueller (2009) find that individual investors who report enjoying investing or gambling turn their portfolios over at twice the rate of their peers. Dorn et al. (2014) report that individual investors treat lotteries as substitutes for speculative financial instruments. Shefrin and Statman (1993) describe individual investors' use of out-of-the-money options with short expiration periods, and note that most of the options they trade expire worthless.[7] As a result, these positions contribute to return patterns that feature both skewness and low rates of realization.

2.2. Judgmental biases and portfolio decisions

Users of technical analysis make predictions by identifying patterns in charts depicting financial data series. To do so, they use tools such as moving averages, concepts such as relative strength, and maxims such as "the trend is your friend" (Mayers, 1989). The pattern-recognition features of technical analysis are highly suited to the formation of judgments about short-term security price movements.[8] In this regard, Roberts (1959) points out that technical analysis can induce judgmental biases as investors identify patterns they mistakenly believe to have predictive value.[9]

Andreassen (1988) reports the results of an experiment in which subjects using price charts are inclined to buy on recent dips and sell after recent price increases. He attributes this behavior to the representativeness[10] heuristic (Kahneman and Tversky, 1972). Andreassen (1987) studies how predictions about whether a trend will continue or reverse are impacted by causal attributes such as news stories that purportedly explain the reason for a past trend. Notably, he finds that the availability of such news leads to predictions that trends will continue.[11]

De Bondt (1993) studies how non-experts use price charts to make stock predictions, and concludes that they are overly prone to "bet on trends." He attributes this feature to representativeness and notes that the bias is stronger when the past trend has been up rather than down.[12]

Consider the psychology literature upon which Andreassen (1987, 1988) and De Bondt (1993) draw. Kahneman and Tversky (1972) explain why people are inclined to commit "gambler's fallacy," in which they make unwarranted predictions of reversal. For example, after observing a long run of heads from tossing a fair coin, people come to believe that "a tail is due" on the next toss. Kahneman and Tversky suggest that when people know the underlying stochastic process, they form

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[5] By speculation, we mean speculation on short-term developments in the stock market.

[6] Shefrin and Statman (1993) discuss how prospect theory provides insights about why investors find options attractive. Using an equilibrium model, Barberis and Huang (2008) discuss how prospect theory provides insights about why investors find securities with positively skewed returns attractive.

[7] In respect to building behavioral portfolios, Shefrin and Statman (1993) discuss evidence from Merrill Lynch about a group of investors who maintained fixed-income accounts, and used all the associated interest to purchase out-of-the-money call options.

[8] Menkhoff and Taylor (2007) connect investment strategy to an investor's investment horizon, with technical analysis being associated with a short horizon relative to other strategies.

[9] Shefrin and Statman (1986) explain why investors are inclined to exhibit the behavior described by Roberts (1959) and not learn over time. According to the discussion of professional investors in Dick and Menkhoff (2013), chartists update their expectations more frequently than fundamentalists. In this respect, Hoffmann, Post, and Pennings (2013) document that updates in expectations drive individual investors' trading frequency.

[10] Representativeness refers to the idea of basing a judgment about an object on the degree to which the object is representative of the features of the underlying population.

[11] Andreassen and Kraus (1990) emphasize the role of variables that make trends salient.

[12] Salient points in charts create more complex patterns. In Appendix A2, we discuss selections from the literature dealing with such patterns.

predictions that they believe are most representative of realizations from the underlying process. In regard to representativeness, they facetiously refer to the concept of falsely expecting the law of large numbers to hold for small samples as "the law of small numbers."

Gilovich et al. (1985) explain why people are prone to make unwarranted predictions of continuation, such as the "hot hand fallacy," where people predict that basketball players who in a particular game have been "hot" will continue to be "hot." Gilovich et al. suggest that when people do not know the underlying process, but must first estimate it in order to make a prediction, they identify a process for which their past observations are most representative. The "law of small numbers" is operative in this context as well. If the most representative process features positive autocorrelation, then they will make predictions consistent with such a process, meaning predictions of continuation, whether warranted or not.

The finance literature provides some evidence about how the issues addressed by Kahneman and Tversky (1972), Gilovich et al. (1985), Andreassen (1987, 1988), and De Bondt (1993) are manifest within the behavior of individual investors. Using data from Finnish financial markets, Grinblatt and Keloharju (2001) document findings about whether individual investors are prone to bet on trends or reversals for histories of approximately one month or longer. In line with Andreassen (1987), they report that Finnish individual investors are generally inclined to bet on reversals in respect to their decision to buy a stock instead of to sell that stock, and to a weaker extent to sell instead of to hold.[13]

Grinblatt and Keloharju report that these findings co-exist with the disposition effect, in which investors tend to hold stocks whose current prices lie below the original purchase price (Shefrin and Statman, 1985). Notably, individual investors tend to sell stocks whose prices have advanced in the prior two days; however, this effect is mitigated for sales that would involve a realized loss, which is consistent with the disposition effect.

In the finance literature, excessive turnover is strongly associated with overconfidence (Barber and Odean, 2000; Glaser and Weber, 2007). Notably, De Bondt (1993) finds that his subjects are overconfident in that they form confidence intervals for their predictions which are too narrow. In addition, his subjects tend to extrapolate past volatility.

Barber and Odean (2001a) link overconfidence and gender. They report that although men and women roughly earn the same returns, men hold riskier portfolios, and therefore earn lower risk-adjusted returns. Barber and Odean attribute this difference to men being more overconfident than women. This suggests that if users of technical analysis are disproportionately overconfident, then there is reason to suspect that men are more inclined to use technical analysis than women.

Anderson (2013) places the discussion of gender into a broader perspective in discussing the impact of overconfidence on portfolio concentration. He applies the term "high stake" to describe investors with highly concentrated portfolios, stating: "High stake investors are, on average, overconfident in their abilities to invest successfully, and they trade more. They have less wealth, are younger, more likely to be men, and have a lower level of education compared with those with less concentrated portfolios." (p. 1723). Using Swedish individual tax data matched with trading records, Anderson provides empirical evidence to support his characterization.

2.3. Concentration, turnover, and the risk-return profile

Anderson (2013) develops a theoretical model that facilitates the analysis of how the speculative motive and judgmental biases combine to impact concentration, turnover, and the risk-return profile of individual investors' portfolios.[14] His model features a conventional mean-variance quadratic utility model, a risk-free asset, a risky benchmark portfolio which is mean-variance efficient relative to publicly available information, and a specific stock which the investor believes holds the potential to generate a positive abnormal return.

The conventional two-fund separation property holds for this model, so that an investor chooses a subjectively optimal mix of a risk-free asset and a risky asset. In this regard, the fraction of the investor's wealth allocated to the risky asset is the product of three terms: (1) the Sharpe ratio of the risky asset; (2) the investor's risk tolerance (also known as risk appetite, the inverse of risk aversion); and (3) return precision (the inverse of return standard deviation).

Anderson (2013) expresses the investor's subjective expected return to the benchmark portfolio as the sum of its mean and a white noise disturbance. He then expresses the investor's expected return for the individual stock as the sum of the return to the benchmark, the expected excess return of the stock over the benchmark, and a white noise disturbance. He assumes that the two disturbance terms are independent.

At every decision time, the investor divides the risky portion of his portfolio into the benchmark and the individual stock. This division determines a ratio of the proportion assigned to the stock divided by the proportion assigned to the benchmark.[15]

[13] Appendix A2 discusses how investors generally react to more complex patterns caused by the presence of salient price points.

[14] Anderson (2013) mentions "overly optimistic investors," but actually makes no reference to overconfidence. Nevertheless, he implicitly models overconfidence in the same way as Odean (1998b), namely higher return precision. For the purpose of clarity, we distinguish between three specific biases as follows: *Excessive optimism* pertains to estimates of mean returns being upwardly biased. *Overconfidence about knowledge* pertains to estimates of return precision being upwardly biased. These two biases are explicit. Implicit is the notion of *overconfidence about investment ability*, particularly stock-picking ability, in that investors believe themselves to be better at these tasks than they actually are. *Overconfidence about investment ability* is a form of the "better-than-average" effect.

[15] The optimal value of the ratio of the overall portfolio weight to the individual stock if it was the only risky asset available to the overall portfolio weight of the benchmark if it was the only risky asset available.

In respect to both the benchmark portfolio and the individual stock, Anderson (2013) examines the impact of excessive optimism by allowing the investor to have upwardly biased estimates of expected returns, and overconfidence by allowing the investor to have upwardly biased estimates of return precision.

In Anderson's framework, excessive optimism leads to a higher perceived Sharpe ratio for the benchmark, and therefore a higher portfolio weight being attached to the risky component. Investor overconfidence about the benchmark's return standard deviation leads not only to a higher perceived Sharpe ratio but also to a higher benchmark precision, both of which imply a higher weight being attached to the risky component of the investor's portfolio.

Both excessive optimism and overconfidence about the individual stock lead the risky component of the portfolio to feature a higher relative allocation to that individual stock. This is why excessive optimism and overconfidence imply greater portfolio concentration.

In Anderson's (2013) model, the weight attached to the risk-free asset depends on overconfidence associated with the benchmark, but not overconfidence associated with the individual stock. Anderson notes that this result is most likely an artifact of his model which does not generalize to other utility functions. For this reason, we assess, rather than hypothesize, the degree to which overconfidence impacts changes in overall portfolio risk.

3. Hypotheses

In this section, we draw on the behavioral literature described in Section 2 to derive hypotheses about the impact of individual investors' use of technical analysis on portfolio concentration, turnover, momentum investing, risk, and returns.

Our first hypothesis pertains to portfolio concentration. Recall that the non-expert subjects in De Bondt (1993) price-chart experiment made point forecasts that were too extreme, and made interval forecasts that were too narrow. In respect to associated trading positions, the point forecasts exhibit excessive optimism and the interval forecasts exhibit overconfidence. By its nature, technical analysis induces its users to identify patterns in singular data, and to predict how those patterns will unfold through time. As Kahneman (2011) points out in his discussion of the planning fallacy, the focus on singular data strongly contributes to excessive optimism and overconfidence in the preparation of project forecasts.

Viewed through the lens of Anderson's (2013) model, excessive optimism and overconfidence imply both an elevated Sharpe ratio and an elevated precision value for the stock relative to the benchmark. Holding risk tolerance constant, higher values for these variables imply a higher portfolio allocation to the stock and therefore greater concentration. This leads us to hypothesize that investors who report using technical analysis will hold more concentrated portfolios than those who do not. We formulate this hypothesis in terms of the "marginal effect of technical analysis," by which we mean that the effect holds even when we control for variables such as age, gender, attitude toward risk bearing and investment objective.[16] Note that the previous remark also holds for all other hypotheses.

H1. The marginal effect of using technical analysis on portfolio concentration is positive.

Consider next the issue of turnover. As the experiments of Andreassen (1987, 1988) and De Bondt (1993) illustrate, investors' predictions about returns and volatility change with the patterns they perceive in recent price charts. In this regard, Andreassen (1987) argues that people overreact to patterns in the data that are salient, such as when news stories provide causal attribution for trends. Notably, these patterns typically change with market movements. Therefore, investors using technical analysis are more prone to revise their predictions about returns and volatility than investors who use other strategies such as fundamental analysis, but not technical analysis.

Viewed through the lens of Shefrin and Statman (2000), investors with the speculative motive have high aspirations and strong needs for upside potential generally, and achieving their high aspiration levels in particular. As a result, they are more prone to use lottery-like securities, such as out-of-the-money options. The previous paragraph suggests that using technical analysis will induce such investors to feature higher turnover for derivatives relative to other investors.

Viewed through the lens of Anderson's (2013) model, the changing patterns in the charts will introduce frequent revisions to investors' estimates for Sharpe ratios and return precision levels. Because perceived Sharpe ratio and return precision are inputs determining portfolio allocations, frequent changes to these values will induce frequent changes in portfolio allocations, thereby giving rise to turnover. Taken together, the remarks in this paragraph, and the two preceding, imply the following hypothesis[17]:

H2. The marginal effect of technical analysis on turnover is positive, both for stocks and for derivatives.

Consider next the issue of betting on trends or reversals. Recall that the experimental subjects studied in Andreassen (1988) predominantly sell on trends, thereby suggesting predictions involving reversal. Andreassen (1988) explains their behavior as the result of representativeness, in the sense of "gambler's fallacy." However, Andreassen (1987) finds that subjects will predict continuation if causal attributions are provided in addition to the information conveyed by price charts.

[16] In controlling for risk tolerance, we note that risk tolerance enters the optimal portfolio decision rule as one of three terms in a product, with the other two being the Sharpe ratio and return precision.

[17] In respect to H1 and H2, we note that Anderson (2013) finds a positive correlation between turnover and portfolio concentration, which he explains as a consequence of his model. Note that in H2, we control for concentration, so that our test is for a property stronger than the statement that H1 implies H2.

These attributions can be media reports. However, they can also be ideas from books on technical analysis explaining that "the trend is your friend," which is a guiding principle of technical analysis. See Mayers (1989).

What appears to be critical in shifting behavior from selling on trends (as in Andreassen, 1988) to betting on trends (as in Andreassen, 1987) is inducing people to change their views of the underlying process. Almost everyone knows that the fair coin toss process features 50–50 odds; therefore, even after a long run of heads, people are not inclined to change their views of the process. However, this is not so for basketball fans observing that a particular player is "hot," where the evidence is consistent with their intuition about the realizations from a positively correlated process. Likewise, this is not true for investors observing a sustained price increase for a given stock, and reading or hearing stories that provide a plausible explanation for the trend. Finally, this is not so for users of technical analysis who have been exposed to the causal attribution that for "hot" stocks, "the trend is your friend."

Trading as if "the trend is your friend" means trading on momentum. Therefore, we hypothesize the following:

H3. The marginal effect of technical analysis on the factor loading for momentum is positive.

Consider next the issue of risk. The specific version of the model developed in Anderson (2013) implies that excessive optimism and overconfidence relating to individual securities do not impact the weight an investor selects for the risky component of his portfolio, or equivalently for the proportion of his portfolio invested in the risk-free asset. As a result, we have no strong priors about the relationship between technical analysis and overall risk, and leave it to the data to so inform us. Hypothesis H3 suggests that increasing the loading on momentum might contribute to an increase in the proportion of systematic risk to total risk. However, the argument involving concentration in Anderson's model implies that relative to the market, excessive optimism and overconfidence about individual securities result in increased exposure to nonsystematic risk, which we state as follows[18]:

H4. The marginal effect of technical analysis on the ratio of nonsystematic risk to total risk is positive.

Finally, consider the impact of technical analysis on returns. We consider three notions of returns: gross returns, net returns, and risk-adjusted returns. Gross returns are raw returns before transaction costs. Net returns are raw returns after transaction costs. Risk-adjusted returns are net returns after adjusting for risk using the Carhart (1997) four-factor model.

The previous hypotheses all have implications for returns. Greater turnover (H2) reduces net returns. Betting on trends (H3) increases gross returns by increasing the loading on momentum. Holding total risk constant, greater concentration (H1) and a lower ratio of systematic risk to total risk (H4) reduces gross returns, net returns, and risk-adjusted returns.

The marginal effect of technical analysis, controlling for concentration and turnover, will reflect costs associated with poor trading decisions related to security selection and market timing. Therefore, our hypothesis about technical analysis and returns is as follows:

H5. The marginal effect of technical analysis is negative for gross returns, net returns, and risk-adjusted returns.

4. Data and methods

4.1. Brokerage records

The brokerage data features clients' opening positions and transaction records. The typical record consists of a client identification number, a buy/sell indicator, the type of asset traded, gross transaction value, and transaction costs. For robustness, we exclude accounts of minors (age <18 years) and accounts with a beginning-of-the-month value of less than €250.

4.2. Survey data

In 2006, the brokerage firm administered a survey among all of its clients and received responses from 6565 investors. We were not involved in the design of the client survey. After we match transaction records with survey data, we obtain a sample of 5500 clients and corresponding accounts for which both transaction and survey data are available.[19]

The survey sought to identify the clients' investment objectives, investing strategies, and a variety of other characteristics and traits. Appendix A3 provides the exact survey questions.

[18] Risk tolerance is one of the terms in Anderson's (2013) three-term portfolio-weight equation for risky assets. In discussing the marginal effect of using technical analysis on risk in H4, we specifically control both for speculation as an investment objective and for risk tolerance (risk appetite). Recall that LLS (1980) report that the typical high roller uses technical analysis and has a short-term focus, suggesting that high rollers have greater risk appetites. However, LLS do not seek to disentangle the separate effects of using technical analysis and maintaining a short-term focus, which leaves open the question of whether, after controlling for investment objective, investors using technical analysis are inclined to choose riskier portfolios. Because our data includes information on whether investors have speculation as a primary objective, we can control for both investment objective and risk appetite when testing H4.

[19] To assess the possible consequences for the main results of investors starting to trade only during the sample period, we performed a robustness check in which we estimate Carhart's alpha and calculate all other variables for the 36-month sub-period of April 2003–March 2006. The results of regressions done on this sub-period are similar to those obtained for the full sample period and the conclusions in terms of main results are identical.

Table 1
Variable definitions.

Variable name	Description
Characteristics and traits	
Male account	Dummy variable: one if the primary account holder is male.
Age	Age in years of the primary account holder in 2006.
Trades	Total number of trades per account per year.
Turnover stocks	Average of the value of all stock purchases and sales in a given month, divided by the beginning-of-the-month account value.
Turnover derivatives	Average of the value of all options purchases and sales in a given month, divided by the beginning-of-the-month account value.
Portfolio value	Average market value of all assets in the investor's portfolio at the end of the sample period.
Experience	Number of months an investor has been trading.
HHI	Herfindahl-Hirschmann Index value for an investor's portfolio. The HHI is defined as the sum of the squared portfolio weights of all assets. For the purpose of the HHI calculations, mutual funds are assumed to consist of 100 equally weighted, non-overlapping positions.
HHI*	Normalized HHI index: (HHI–(1/N))/(1–(1/N)).
Gross/net returns	Gross and net performance according to Eqs. (1) and (2), respectively.
Novice/advanced/very advanced investor	Dummy variables for self-assessed investment skill: one if an investor reports to be a novice, advanced, or very advanced investor, respectively.
Risk appetite	Self-reported risk-taking tendency on a scale ranging from 1 = I am a very conservative investor to 7 = I am a very speculative investor.
Ambition	Self-reported ambition level on a scale ranging from 1 = I am not ambitious to 5 = I am very ambitious.
Investing strategies	
Technical analysis	Dummy variable: one if respondent reports to use this strategy.
Fundamental analysis	Dummy variable: one if respondent reports to use this strategy.
Professional advice	Dummy variable: one if respondent reports to use this strategy.
Intuition	Dummy variable: one if respondent reports to use this strategy.
Investment objectives	
Saving for retirement	Dummy variable: one if respondent reports this as most important investment objective.
Hobby (entertainment)	Dummy variable: one if respondent reports this as most important investment objective.
Building financial buffer	Dummy variable: one if respondent reports this as most important investment objective.
Speculation (gambling)	Dummy variable: one if respondent reports this as most important investment objective.
Capital growth	Dummy variable: one if respondent reports this as most important investment objective.

An issue that arises with survey data is that investors' objectives and strategies are self-reported. A reasonable question one might ask is whether investors understand what is meant by fundamental and technical analysis, and whether they know the difference between the two. For our data, there are at least two reasons to believe that survey participants are able to correctly identify their investment objectives and strategies. First, every new client of the brokerage firm receives a start-up manual that not only explains how to log in to their account and complete transactions, but also clarifies the differences among several common investment strategies, such as fundamental versus technical analysis. Appendix A4 contains excerpts from this manual. Second, before they can make their first transaction, clients must pass an online test checking whether they have at least a basic knowledge of investing. This test includes questions on the difference between fundamental and technical analysis.

4.3. Summary statistics

Table 1 provides definitions of all variables. Table 2 provides descriptive statistics. Of the sample of 5500 investors for which both transaction records and survey data are available, 77% are male and the mean age is about 50 years. The mean (median) number of trades per year is 10.7 (4.7). Average (median) monthly stock turnover is about 23% (10%); for derivatives such as option contracts, it is 9.9% (3.2%).

The average (median) portfolio value at the end of the sample period is €45,915 (€15,234). A comparison of the average portfolio value of sampled investors with the total portfolio value of the average Dutch investor (Millward-Brown, 2006) indicates that our average respondent invests more than three-fourths of his total self-managed investment portfolio at this particular broker. In fact, over 40% of our survey respondents only hold an investment account at this particular broker. Of the respondents who also hold an investment account at another broker, more than 50% indicate that the assets in that other account comprise less than one half of their total portfolio. As a robustness check, we compare the results of investors who invest only through this particular broker with those who also have another broker and find no significant differences.

Mean (median) trading experience is 40.2 (39.0) months. To assess investors' portfolio concentration, we use the Herfindahl-Hirschmann Index (HHI). For the purpose of the HHI calculations, we follow Dorn and Huberman (2005) and Dorn

Table 2
Descriptive statistics. This table presents descriptive statistics for a sample of 5500 investor accounts at a Dutch online broker. The sample period is from January 2000 to March 2006. Variables are defined in Table 1. The table shows the mean, median, and standard deviation for each variable, as well as 5th, 25th, 75th, and 95th percentile values.

Mean	Std.	Dev	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
Male account	0.77						
Age (in years as of 2006)	49.70	12.73	28.00	40.00	50.00	59.00	70.00
Trades (# per year)	10.66	17.65	0.17	1.50	4.66	12.17	43.06
Turnover stocks (% per month)	23.03	33.34	0.00	3.65	10.03	26.39	98.19
Turnover derivatives (% per month)	9.85	24.48	0.00	0.00	3.20	6.69	51.92
Portfolio value (€)	45,915	142,576	1057	5321	15,234	42,406	166,840
Experience (months)	40.21	20.91	9.00	22.00	39.00	60.00	72.00
HHI (%)	27.78	23.28	1.10	9.80	21.14	39.73	78.42
HHI* (%)	17.20	21.55	0.16	4.06	9.06	20.74	70.69
Monthly gross returns	0.004	0.052	−0.048	−0.006	0.006	0.017	0.052
Standard deviation of gross returns	0.086	0.088	0.014	0.036	0.066	0.109	0.213
Monthly net returns	−0.002	0.055	−0.058	−0.009	0.003	0.013	0.039
Standard deviation of net returns	0.085	0.086	0.014	0.036	0.066	0.109	0.213

and Sengmueller (2009), and assume that mutual funds consist of 100 equally weighted, non-overlapping positions.[20] The mean (median) Herfindahl-Hirschmann Index (HHI) is 27.8% (21.1%). Comparing the HHI with the normalized HHI (HHI*) indicates that portfolio weights are not uniformly distributed.[21] Mean (median) monthly net returns over the sample period are −0.20% (0.30%).

4.4. Measuring investor performance

Investor performance is the monthly change in market value of all securities in an account net of transaction costs. As performance is measured on a monthly basis, assumptions must be made regarding the timing of deposits and withdrawals of cash and securities. As in Bauer et al. (2009), we assume that deposits are made at the start of each month and withdrawals take place at the end of each month. We obtain similar results if we assume that deposits and withdrawals are made halfway during the month. Hence, we calculate net performance as:

$$R_{it}^{net} = \frac{V_{it} - V_{it-1} - NDW_{it}}{V_{it-1} + D_{it}} \tag{1}$$

where V_{it} is the account value at the end of month t, NDW_{it} is the net of deposits and withdrawals during month t, and D_{it} are the deposits made during month t.

Gross performance is obtained by adding back transaction costs incurred during month t, TC_{it}, to end-of-the-month account value,

$$R_{it}^{gross} = \frac{V_{it} - V_{it-1} - NDW_{it} + TC_{it}}{V_{it-1} + D_{it}}, \tag{2}$$

4.5. Investor performance attribution

To obtain investors' risk-adjusted performance, we attribute their returns using the Carhart (1997) four-factor model. This model adjusts returns for exposure to market (RM), size (SMB), book-to-market (HML), and momentum (MOM) factors. Motivated by Griffin (2002), we construct these factors for the Dutch market, as our sample of investors invests mainly in Dutch securities.[22]

When forming the factor-mimicking portfolios, we follow Bauer et al. (2005), and consider all stocks in the Worldscope Netherlands universe. Using the online research tool by Style Research Ltd, we construct the SMB and HML factors according to the procedure described on the website of Kenneth French,[23] and the MOM factor according to the procedure described by Carhart (1997). As in Bauer et al. (2005), all factor portfolios are value-weighted. The market return in the RM factor is the return on the Worldscope Netherlands universe. On average, the monthly return on the Dutch market is −0.06% during the sample period, with a standard deviation of 5.56%.

[20] The failure to make this assumption would lead one to draw inappropriate conclusions about investors' portfolio concentration. For example, one would then judge the portfolio of an investor holding two individual common stocks and the portfolio of an investor holding two mutual funds to be equally concentrated, although in reality, the latter portfolio is substantially more diversified.

[21] HHI* measures HHI relative to a uniform benchmark, thereby facilitating comparisons across portfolios with different numbers of stocks. The HHI*-benchmark value for a uniformly distributed portfolio is zero.

[22] In terms of volume (value), 95% (85%) of all trades by our sample of investors are in Dutch securities.

[23] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 3
High Rollers Relative to Other Investors – LLS vs. This Study. This table compares the characteristics of high rollers relative to other investors in the LLS data to the characteristics of high rollers relative to other investors in our data. Variables are defined in Table 1.

	LLS (1980)	This study (2014)
Sample period	1964–1970	2000–2006
Turnover	15 times higher than other investors	16 times higher than other investors
Performance (risk-adjusted)	4.1% lower than other investors	15% lower than other investors
Use of technical analysis as strategy	58% more likely than other investors	37% more likely than other investors
Use of fundamental analysis as strategy	51% less likely than other investors	5% more likely than other investors
Systematic risk	18% higher than other investors	19% higher than other investors
Transaction costs	5 times higher than other investors	2 times higher than other investors

The following time-series model is estimated to obtain risk-adjusted returns:

$$R_{it} = \alpha_i + \sum_{k=1}^{K} \beta_{ik} F_{kt} + \varepsilon_{it}. \tag{3}$$

In this model, R_{it} represents the return in excess of the risk-free rate on investor i's portfolio. Following Bauer et al. (2005), the risk-free rate is the return on the one-month interbank rate. B_{ik} is the loading of portfolio I on factor k, and F_{kt} is the month t excess return on the k-th factor-mimicking portfolio. The intercept α_i measures individual investors' performance relative to the risk and style factors. The factor loadings indicate whether a portfolio is tilted toward market risk or a particular investment style, such as investing in value versus growth stocks, for example. To avoid potentially biased estimates, we impose a minimum number of return observations of 36 months per investor when estimating (3).

4.6. Comparison of our data with data used by LLS

Appendix A5 contains a detailed comparison between our data and the data used by LLS (1974, 1976, 1977, 1978a,b, 1980) and Barber and Odean (2000, 2002), respectively. Here we highlight key issues about similarities and differences between our data and the LLS data.

Consider high rollers, which LLS (1980) define as the quintile of investors associated with the highest turnover, and which they associated with the use of technical analysis. LLS (1980) indicate that relative to other investors, high rollers turn over their portfolios by a factor of 15, underperform by 4.1% on a risk-adjusted annual basis, are 58% more likely to report using technical analysis, are 51% less likely to report using fundamental analysis, take on 18% more systematic risk, and incur annual transaction costs that are five times higher. Our data on high rollers share the same patterns as the LLS (1980) data, with stronger effects for net returns and weaker effects for fundamental analysis and transaction costs (Table 3).[24]

In the LLS (1974) sample, 27% of investors report using technical analysis either exclusively or in combination with another strategy, whereas in our sample, the corresponding figure is 32%. If we confine our attention to investors who report using technical analysis exclusively, the figure for the LLS (1974) sample is 4%, whereas in our sample it is 9%. As for intuition, at most 4% of investors in the LLS (1974) sample indicate that they base their investment decisions on some "other personal approach," which comes closest to relying on their own intuition, whereas 19% of the investors in our sample report relying solely on their intuition. For a graphical contrast of the two datasets, see Fig. 1.

According to LLS (1974), the typical individual investor is "primarily a 'fundamental' analyst who perceives himself to hold a balanced, and well-diversified, portfolio of income and capital-appreciation securities" (p. 424). As Fig. 1 shows, LLS (1974) find that roughly 65% of investors in their sample report having based their investment decisions on fundamental analysis. In comparison, the corresponding figure in our sample is a much lower 20%.

5. Results

We test our hypotheses by reporting regression results explaining portfolio concentration, turnover for stocks and derivatives, exposure to the momentum factor from the Carhart (1997) four-factor model, risk (standard deviation of gross and net returns, and adjusted R^2 of Carhart regressions),[25] and returns (gross, net, and risk-adjusted). In addition to regressions, we test some hypotheses using differences in means for particular populations. In the regressions, we control for a variety

[24] In comparison with other investors, high-rollers in our data take approximately 43% more total risk as measured by return standard deviation. Also, LLS use the CAPM to compute systematic risk, whereas we use the Carhart four-factor model.

[25] According to Amihud and Goyenko (2013), the R^2 of the Carhart four-factor model indicates the proportion of return variance that is explained by the variation in these four risk- and style factors. As such, $1 - R^2$ indicates the proportion of return variance that is due to nonsystematic risk. Negative coefficients in regressions in which R^2 is the dependent variable thus indicate that investors take more nonsystematic risk (as a lower proportion of their returns are explained by the Carhart four-factor model), while positive coefficients indicate that investors take less nonsystematic risk (as a higher proportion of their returns are explained by the Carhart four-factor model).

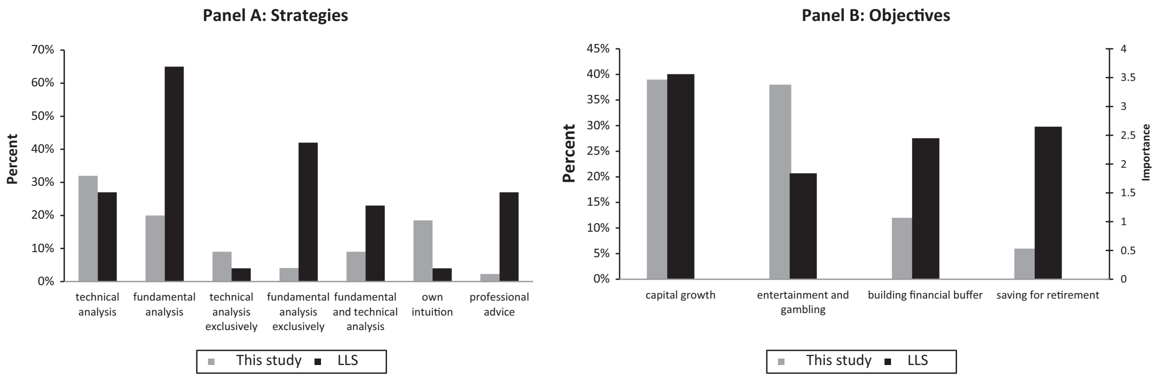

Fig. 1. Investor strategies and objectives. Panel A of this figure highlights the differences between the distribution of strategy usage of the 5500 individual investors in this study of which we have both brokerage and survey data and that of the 972 investors in LLS. In our study's survey, investors could report using multiple strategies, whereas in LLS they could indicate only their most frequently used strategy. Investors in LLS and our sample who report using technical analysis either exclusively or in combination with another strategy are classified as using technical analysis. Investors in LLS and our sample who report using fundamental analysis either exclusively or in combination with another strategy are classified as using fundamental analysis. Investors in LLS and our sample who report using technical analysis exclusively are classified as using technical analysis exclusively. Investors in LLS and our sample who report using fundamental analysis exclusively are classified as using fundamental analysis exclusively. Investors in LLS and our sample who report using fundamental analysis in combination with technical analysis are classified as using fundamental and technical analysis. Investors who report relying only on their own intuition are matched to investors in LLS who report using some "other personal approach." Investors who report relying on a professional advisor are matched to investors who in LLS report relying on their brokerage firm or account executive's recommendation or the advice of a paid investment newsletter or investment counselor. Panel B of this figure highlights the differences between the distribution of the primary investment objective of the 5500 individual investors in this study of which we have both brokerage and survey data and that of the 972 investors in LLS. Note that this study asks respondents to indicate their most important investment objective, whereas LLS ask respondents to rate the objectives in terms of importance on a scale from 1 = irrelevant to 4 = very important. Capital growth is compared to LLS's long-term capital appreciation, entertainment and gambling refer to investing as a hobby and for speculation, and are compared to LLS's short-term capital gains; building a financial buffer is compared to LLS's intermediate-term capital appreciation; and saving for retirement is compared to LLS's dividend income.

of characteristics and traits that are possible drivers of investor behavior and performance, such as age, trading experience, gender, self-assessed investment skill, risk appetite, ambition levels, and portfolio size (see Tables 4–9).[26,27]

5.1. Concentration

We test H1 in two ways, with the first based on regression results. Table 4 shows regression results for investors' portfolio concentration (HHI). These results provide support for H1, as the coefficient on technical analysis is positive and significant. Specifically, the marginal effect of reporting the use of technical analysis is to increase HHI by 3.4%.

Our second test for H1 involves ascertaining the effect on concentration of investors using technical analysis in addition to other strategies. Table 5 shows that adding technical analysis to professional advice features higher concentration, but for intuition and fundamental analysis, the result is not statistically significant.

5.2. Turnover

Table 6 shows that technical analysis is positively and significantly related to turnover of both stocks and derivatives, thereby supporting H2. The marginal effect of reporting the use of technical analysis is to increase monthly stock turnover by 6.9% and monthly derivatives turnover by 13.1%.

Regarding the control variables, we find that speculation as an objective is positively associated with turnover of both stocks and derivatives. The marginal effect of an investor reporting that his primary investment objective is speculation is to increase monthly turnover for stocks by 22.6% and for derivatives by 19.2%. Furthermore, investors with higher ambition levels and investors who hold more concentrated portfolios trade more, which is consistent with Goetzmann and Kumar (2008). In addition, wealthier investors have a higher turnover of stocks, but a lower turnover of derivatives. This finding appears consistent with the notion that wealthier investors are more sophisticated, as prior work by Bauer et al. (2009) using the same data reports that option trading hurts performance. Alternatively, the result may indicate that trading options is a way for less wealthy investors to get exposure to the stock market. Consistent with Dorn and Huberman (2005), more experienced investors trade less frequently, while investors with a higher risk appetite trade more frequently.

[26] LLS (1977) state: "By far the most dominant elements in the story are investor age, income level, and sex, essentially in that descending order of importance. . ." (p. 304). With respect to our data, trading experience and portfolio size have strong effects, but for most regressions, we do not find a significant effect for gender.

[27] As a robustness check, we repeated all our analyses without including portfolio size as a control variable, and find that our major conclusions about the effect of technical analysis are unaffected.

Table 4
Portfolio concentration.

	HHI	
	Coeff	*t*-stat
Intercept	1.044 ***	10.45
Characteristics and traits		
Age (years)	−0.001 *	−1.83
Experience (months)	−0.001 ***	−3.06
Male account	0.002	0.18
Novice investor	0.032	0.40
Advanced investor	0.018	0.22
Very advanced investor	0.041	0.50
Risk appetite	0.000	−0.12
Ambition level	−0.005	−0.80
Log portfolio value (€)	−0.058 ***	−14.01
Turnover stocks	0.046 ***	9.48
Turnover derivatives	0.013	1.63
Strategies		
Technical analysis	0.034 ***	2.93
Fundamental analysis	−0.022 *	−1.69
Professional advice	−0.048 ***	−2.73
Intuition	0.006	0.54
Objectives		
Saving for retirement	−0.069 **	−2.07
Hobby	−0.024	−0.84
Building financial buffer	−0.043	−1.41
Speculating	−0.018	−0.57
Capital growth	−0.067 **	−2.41
Adj. R^2		0.123
No of Observations		5500

This table reports cross-sectional regression estimates to explain investor portfolio concentration, as expressed by the Herfindahl-Hirschmann Index (HHI) value of their portfolio. Variables are defined in Table 1.

* Statistical significance at 10%.
** Statistical significance at 5%.
*** Statistical significance at 1%.

Table 5
Incremental effects of adding technical analysis to another investing strategy.

Key variables	Fundamental analysis		Own intuition		Professional advice	
	Impact	*t*-stat	Impact	*t*-stat	Impact	*t*-stat
Alpha	−0.001	−0.49	−.001	−0.65	−0.006*	−1.76
RM	0.024	0.39	.065	1.44	0.172	1.40
SMB	−0.026	−0.57	−.058*	−1.67	0.066	0.66
HML	0.061	1.61	.032	1.12	0.002	0.02
MOM	0.027	0.96	.054**	2.56	−0.028	−0.58
Adj. R^2 Carhart Regression	−0.034**	−2.19	−.015	−1.22	−0.018	−0.50
Age (years)	1.510**	1.96	.707	1.30	−2.064*	−1.85
Experience (months)	−5.949***	−4.53	−4.827***	−5.46	−7.738***	−4.13
Turnover stocks	0.134**	2.13	.180***	3.58	0.428***	4.04
Turnover derivatives	0.075***	2.88	.158***	4.85	0.219***	3.96
Portfolio value (€)	−17,504*	−1.80	4155	0.60	−21,710*	−1.81
Gross returns (monthly)	−0.002	−0.67	−.004	−1.58	−0.009*	−1.86
Net returns (monthly)	−0.006*	−1.67	−.010***	−3.81	−0.016***	−3.05
HHI	0.036	1.56	.029*	1.69	0.076**	2.17
Standard deviation of gross returns	−0.003	−0.68	.015***	3.82	0.010	1.38
Standard deviation of net returns	−0.003	−0.71	.015***	3.85	0.011	1.42

This table reports the incremental effects on key variables from adding technical analysis to the other investing strategies (fundamental analysis, own intuition, and professional advice). The values in this table are computed as follows: For each column in the table, for example, the column "fundamental analysis", we first calculate the listed key variables for the group of investors in the sample that use this particular strategy *without* technical analysis. Then, we calculate these variables for the group of investors in the sample that use this particular strategy *with* technical analysis. Finally, we use *t*-tests to compare the difference between the key variables for these two groups of investors and assess the statistical significance of this difference. We report the difference regarding the listed key variables between these two groups of investors (i.e., investors using a particular strategy without technical analysis and investors using a particular strategy with technical analysis) and the *t*-stat from the *t*-test.

* Statistical significance at 10%.
** Statistical significance at 5%.
*** Statistical significance at 1%.

Table 6
Turnover.

	Turnover stocks		Turnover derivatives	
	Coeff	*t*-stat	Coeff	*t*-stat
Intercept	−.414	−1.25	.213	1.02
Characteristics and traits				
Age (years)	−.001	−0.79	.002 **	2.08
Experience (months)	−.003 ***	−3.13	−.002 ***	−4.38
Male account	−.011	−0.30	.033	1.50
Novice investor	−.079	−0.29	−.048	−0.28
Advanced investor	−.089	−0.33	.052	0.31
Very advanced investor	−.235	−0.86	.112	0.65
Risk appetite	.032 ***	2.98	.015 **	2.27
Ambition level	.032 *	1.72	.022 **	1.91
HHI	.497 ***	9.46	.050	1.51
log portfolio value (€)	.066 ***	4.74	−.039 ***	−4.54
Strategies				
Technical analysis	.069 *	1.81	.131 ***	5.47
Fundamental analysis	.000	0.01	−.077 ***	−2.85
Professional advice	.004	0.07	.052	1.44
Intuition	.081 **	2.37	−.026	−1.20
Objectives				
Saving for retirement	−.233 **	−2.13	.077	1.12
Hobby	−.065	−0.70	.062	1.06
Building financial buffer	−.166 *	−1.66	.044	0.70
Speculating	.226 **	2.24	.192 ***	3.03
Capital growth	−.161 *	−1.75	.051	0.89
Adj. R^2		0.050		0.043
No of Observations		5500		5500

This table reports cross-sectional regression estimates to explain investors' monthly turnover of stocks and derivatives, respectively. Variables are defined in Table 1.

Most investors who use technical analysis do so in combination with some other strategy. Specifically, 23% of the investors in our sample use technical analysis in conjunction with some other strategy, whereas only 9% of the investors in our sample use technical analysis by itself. As in LLS (1974), we examine the effects of combining technical analysis and fundamental analysis. In addition, we examine the use of technical analysis in combination with intuition and professional advice. The amount by which the reported use of technical analysis adds to each strategy is displayed in Table 5.

Table 5 indicates that stock turnover for investors who report using technical analysis in combination with fundamental analysis is 13.4% greater than for investors using fundamental analysis without technical analysis. The analogous figure for derivatives turnover is 7.5%. Both figures are statistically significant at the 1% level of significance. As can also be seen from Table 5, the same general pattern is true for the strategies intuition and professional advice. Notice that the figures associated with professional advice are strikingly high.

5.3. Momentum

Factor loadings on momentum (MOM) provide information about the degree to which individual investors bet on trends. Table 7 shows that the use of technical analysis has a positive and significant effect on the factor loading on MOM, providing support for H3.[28]

To the extent that adding technical analysis to another investing strategy injects a trend-following component into investors' predictions, Table 5 indicates that adding technical analysis to fundamental analysis, intuition and professional advice is associated with higher factor loadings on MOM; however, only the effect on intuition is statistically significant.

The factor loading on MOM associated with the average investor in our data is −0.17, a figure which is significantly different from zero (p = 0.00, t = −26.40). Consistent with the experimental results in Andreassen (1988) and the empirical results in Grinblatt and Keloharju (2001), this negative factor loading on MOM indicates that the average investor in our data trades as if they believe in short-term reversals, meaning that recent winners will subsequently underperform.

In general, investors who report using technical analysis do not bet on trends, but instead bet less on reversals than other investors. The factor loading on MOM associated with investors using technical analysis is −0.13.[29] Among high derivative

[28] Table 7 also shows that technical analysis has a positive effect on the factor loading on HML, suggesting that investors who use technical analysis have a preference for value stocks.

[29] The MOM loading for investors using technical analysis is significantly different from that of the average investor in our data (p = 0.01, t = 2.60), and significantly different from zero (p = 0.00, t = −8.90). Notably, the difference in MOM factor loading between investors using technical analysis and all others is relatively small.

Table 7
Factor loadings.

	RM		SMB		HML		MOM	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Intercept	1.207***	4.49	.092	0.43	.227	1.17	−.182	−1.34
Characteristics and traits								
Age (years)	.001	1.09	−.001	−1.24	.002**	2.22	.002***	2.81
Experience (months)	.003**	2.56	.007***	6.74	−.006***	−7.07	−.001	−1.18
Male account	.063**	2.23	.005	0.21	−.020	−0.97	−.011	−0.76
Novice investor	−.015	−0.07	.119	0.71	−.089	−0.59	−.089	−0.84
Advanced investor	.070	0.34	.120	0.72	−.097	−0.64	−.109	−1.03
Very advanced investor	.041	0.19	.166	0.96	−.123	−0.79	−.122	−1.11
Risk appetite	.042	5.06	.010	1.56	−.003	−0.51	−.008*	−1.83
Ambition level	.030	2.00	.014	1.15	.007	0.63	.001	0.16
HHI	−.065	−1.37	.006	0.15	−.063*	−1.81	−.084***	−3.47
Log portfolio value (€)	−.071***	−5.79	−.050***	−5.04	.012	1.37	.009	1.51
Turnover stocks	.265***	11.68	.130***	7.13	.032**	1.98	−.033***	−2.85
Turnover derivatives	.799***	9.08	−.278***	−3.94	−.061	−0.96	.150***	3.36
Strategies								
Technical analysis	−.001	−0.02	−.006	−0.24	.055**	2.27	.066***	3.90
Fundamental analysis	−.064*	−1.83	.019	0.68	.038	1.51	.024	1.36
Professional advice	−.031	−0.61	.089**	2.16	−.044	−1.18	.029	1.12
Intuition	.008	0.30	.008	0.34	−.025	−1.25	−.016	−1.13
Objectives								
Saving for retirement	−.017	−0.19	−.011	−0.16	.012	0.19	.097**	2.15
Hobby	.074	0.94	.074	1.16	.045	0.79	.005	0.13
Building financial buffer	.043	0.52	−.001	−0.01	−.013	−0.22	.010	0.25
Speculating	.106	1.18	.000	0.01	.046	0.71	.036	0.79
Capital growth	.038	0.50	.041	0.66	−.011	−0.20	.047	1.21
Adj. R^2		0.199		0.079		0.039		0.052
No of Observations		5500		5500		5500		5500

This table reports cross-sectional regression estimates to explain the factor loadings of investors' returns (RM, SMB, HML, MOM). Variables are defined in Table 1.

* Statistical significance at 10%.

** Statistical significance at 5%.

*** Statistical significance at 1%.

rollers, defined as the quintile of investors associated with the highest derivatives turnover, the factor loading on MOM is −0.17, but for high derivative rollers who also use technical analysis, the factor loading is −0.09. The loading on MOM for investors who use technical analysis exclusively is −0.13, and in line with Andreassen (1987), investors who report relying on both news and technical analysis have a MOM factor loading of −0.12.[30]

Overall, we conclude that the use of technical analysis induces individual investors to be less inclined to sell on trends than they would be by using other strategies.

5.4. Risk

Table 8 shows that using technical analysis significantly increases the ratio of nonsystematic risk in investors' total risk exposure, as suggested by H4.[31] Table 8 also shows that technical analysis has a 30 basis-point impact on total risk, as measured by the standard deviation of gross and net returns, but the effect is not statistically significant.

Regarding the control variables, the marginal effect of an investor who reports speculation as his primary objective is to increase the monthly net return standard deviation by 1.8%. Consistent with Dorn and Huberman (2005) and Dorn and Sengmueller (2009), investors in our data who take more risk are associated with more experience, a higher risk appetite, higher ambition levels, more concentrated portfolios, smaller portfolios, and higher turnover.

[30] While suggestive, these loading coefficients are not statistically different from the average loading coefficient for all investors who report using technical analysis. Among high derivative rollers, the factor loading for MOM for investors who exclusively use technical analysis and news is 0.0073, but this subsample's size is very limited.

[31] The mean monthly standard deviation of both gross and net returns is .086. The mean R^2 on the Carhart factor regression is 62.3% (median = 63.3%). The unstandardized impact of technical analysis on the R^2 on the Carhart factor regression is −0.024, implying that technical analysis reduces the percentage of total risk that is systematic by 3.8%.

Table 8
Risk.

	Gross return Standard Deviation		Net Return Standard Deviation		Adj. *R*-Squared Carhart	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Intercept	.033	1.32	.032	1.29	.455***	6.02
Characteristics and traits						
Age (years)	.000	−0.20	.000	−0.21	.000	0.96
Experience (months)	.002***	24.81	.002***	25.01	−.001**	−2.49
Male account	−.003	−1.13	−.003	−1.17	−.015*	−1.86
Novice investor	−.003	−0.14	−.003	−0.16	−.041	−0.70
Advanced investor	.004	0.20	.004	0.17	−.052	−0.88
Very advanced investor	.014	0.68	.013	0.64	−.093	−1.52
Risk appetite	.005***	6.49	.005***	6.38	−.004*	−1.72
Ambition level	.004**	2.64	.004***	2.73	−.005	−1.27
HHI	.025***	6.30	.026***	6.35	−.077***	−5.71
Log portfolio value (€)	−.008***	−7.78	−.008***	−7.65	.033***	9.67
Turnover stocks	.012***	9.56	.011***	9.20	−.036***	−5.56
Turnover derivatives	.024***	12.04	.022***	11.52	−.086***	−3.46
Strategies						
Technical analysis	.003	0.91	.003	1.06	−.024***	−2.60
Fundamental analysis	−.004	−1.35	−.005	−1.46	.010	0.98
Professional advice	.000	0.08	.000	0.11	−.013	−0.91
Intuition	.003	1.17	.003	1.24	.000	0.05
Objectives						
Saving for retirement	.000	0.04	.000	−0.01	.012	0.47
Hobby	.006	0.91	.006	0.91	−.004	−0.18
Building financial buffer	.001	0.18	.001	0.15	−.002	−0.10
Speculating	.018**	2.40	.018**	2.37	−.022	−0.86
Capital growth	.001	0.08	.000	0.06	.007	0.33
Adj. R^2		0.217		0.215		0.169
No of Observations		5500		5500		5500

This table reports cross-sectional regression estimates to explain investors' risk-taking (standard deviation of monthly gross returns, standard deviation of monthly net returns, Adjusted R^2 Carhart's alpha regression). Variables are defined in Table 1.
* Statistical significance at 10%.
** Statistical significance at 5%.
*** Statistical significance at 1%.

5.5. *Returns*

Table 9 indicates that using technical analysis as an investing strategy has a negative and significant effect on gross, net, and risk-adjusted returns (Carhart's alpha), thereby supporting H5.

Regarding the control variables, we find that portfolio concentration (Goetzmann and Kumar, 2008) and turnover (Barber and Odean, 2000) hurt performance, while investors with larger portfolios do better (Dhar and Zhu, 2006). Of course, the latter result could be affected by the fact that better returns lead to larger portfolios. In addition, we find that investors with more trading experience (account tenure) achieve worse returns than investors with less experience, suggesting that experience may lead to overconfidence (Gervais and Odean, 2001; Barber and Odean, 2001a). Finally, consistent with Chalmers and Reuter, 2012; Hoechle et al. (2013), and Karabulut (2013) we find that professional advice hurts investor performance.

Taken together, these results make clear that there are several effects which lead investors using technical analysis to have lower returns than most other investors. For our sample as a whole, our strongest findings about technical analysis involve a −60 basis-point effect on gross monthly returns and a −50 basis-point effect on net monthly returns. These results control for concentration and turnover, and are statistically significant at the 1% level. The 10 basis-point difference between gross and net return effects is not statistically significant.

The lower returns associated with technical analysis stem from exposure to nonsystematic risk, not systematic risk. To see why, notice from Table 7 that the portfolios of investors who use technical analysis feature higher factor loadings on HML and MOM. Because the returns to HML and MOM were positive during our sample period, these higher loadings generated higher returns, not lower returns. The effect of technical analysis on the factor loadings for RM and SMB is small and statistically insignificant. Therefore, the lower returns associated with technical analysis do not stem from differential factor loadings.

We also investigate whether investors using technical analysis bear less systematic risk in total than other investors, even though they bear less systematic risk as a proportion of total risk. We find no evidence of this being the case, and conclude that the lower returns associated with technical analysis stem from exposure to nonsystematic risk.

According to the rightmost column in Table 9, technical analysis lowers risk-adjusted returns (Carhart's alpha) by 20 basis points. Note that the magnitude of this effect is weaker than the effects for gross and net returns, and is only statistically significant at the 10% level.

Table 9
Returns.

	Gross return		Net return		Carhart's Alpha	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Intercept	−0.028 **	−2.20	−0.051 ***	−3.80	−0.011	−1.55
Characteristics and traits						
Age (years)	0.000	−0.40	0.000	−0.54	0.000	0.94
Experience (months)	0.000 ***	−13.27	0.000 ***	−10.62	0.000 ***	−3.79
Male account	−0.002	−1.39	−0.002 *	−1.71	0.001	1.26
Novice investor	0.015	1.43	0.016	1.49	−0.004	−0.68
Advanced investor	0.011	1.09	0.011	0.99	−0.004	−0.79
Very advanced investor	0.004	0.35	0.002	0.18	0.001	0.12
Risk appetite	0.001 *	1.87	0.000	0.82	0.000	0.43
Ambition level	0.000	0.60	0.000	0.19	−0.001 *	−1.69
HHI	−0.007 ***	−3.22	−0.008 ***	−3.76	−0.001	−1.11
Log portfolio value (€)	0.004 ***	8.06	0.007 ***	11.54	0.002 ***	7.00
Turnover stocks	0.002 ***	2.72	−0.001 **	−2.15	−0.008 ***	−13.49
Turnover derivatives	0.001	1.41	−0.010 ***	−9.14	−0.010 ***	−4.32
Strategies						
Technical analysis	−0.005 ***	−3.35	−0.006 ***	−3.81	−0.002 *	−1.78
Fundamental analysis	0.002	0.95	0.002	1.01	0.000	−0.42
Professional advice	−0.006 ***	−2.75	−0.007 ***	−2.85	−0.003 **	−2.33
Intuition	0.000	−0.13	0.000	−0.09	−0.001	−1.26
Objectives						
Saving for retirement	−0.001	−0.28	−0.001	−0.32	0.001	0.37
Hobby	0.003	0.83	0.003	0.89	0.000	−0.05
Building financial buffer	0.000	0.09	0.001	0.25	0.001	0.64
Speculating	−0.001	−0.28	−0.003	−0.70	−0.001	−0.24
Capital growth	0.000	−0.11	0.000	0.07	0.001	0.69
Adj. R^2		0.071		0.103		0.181
No of Observations		5,500		5,500		5,500

This table reports cross-sectional regression estimates to explain investors' monthly gross returns, investors' monthly net returns, and investors' monthly risk-adjusted returns (Carhart's alpha), respectively. Variables are defined in Table 1.
* Statistical significance at 10%.
** Statistical significance at 5%.
*** Statistical significance at 1%.

When we focus attention on high derivative rollers, a clearer picture emerges, as there is a regime-change effect. The regression results reported in Table A6.1 of Appendix A6 show that for this particular subsample of investors, the magnitude of the technical analysis effect on both gross and net returns is -140 basis points. This is approximately two and a half times larger than the effect for the entire sample. The fact that the magnitude of the effect is the same for both gross and net returns suggests that the effect is not due to transaction costs. Notably, the effect of technical analysis on risk-adjusted returns (Carhart's alpha) is −130 basis points ($p = 0.00$, $t = -3.10$), which is close to the −140 basis points for raw returns, although we note that the difference is statistically significant. This relatively small difference suggests that the effect of technical analysis on returns stems mostly, if not completely, from poor portfolio selection and timing. Among high derivative rollers, the additional cost from turnover induced by technical analysis is 29 basis points.

For non-high derivative rollers, we find a technical analysis effect of −20 basis points for both gross and net returns, and −10 basis points for Carhart's alpha (untabulated). None of these effects are significant. Therefore, the technical analysis effect on returns is completely concentrated within high derivative rollers. See Section 6.4 for related regime-change effects.

Basically, high derivative rollers who do not use technical analysis earn 56 basis points per month of risk-adjusted return less than investors who are not high derivative rollers, regardless of whether the latter use technical analysis. Our study indicates that technical analysis dramatically accentuates the poor risk-adjusted performance of high derivative rollers by an additional −130 basis points on average.

The above discussion links poor decisions about stock selection and market timing to a combination of technical analysis and high derivative turnover. In this regard, Bauer et al. (2009), analyzing data from the same source that we use, find inferior returns associated with option trading. They attribute this finding to "bad market timing that results from overreaction to past stock-market movements." (p. 732).[32] In addition, investors who use technical analysis hold more out-of-the-money options, which according to Bauer et al. (2009) likely expire worthless,[33] a feature that is consistent with Shefrin and Statman (1993).

[32] Our results for returns parallel a finding by Odean (1999), who reports that the post-transaction returns of stocks that investors purchase are below the returns of stocks that they sell. Odean attributes this finding to either inferior stock selection or inferior market timing.

[33] We thank the authors of Bauer et al. (2009), who in private communication shared this observation with us.

As Dorn et al. (2014) state, investors who like to gamble favor stocks with positively skewed payoffs. Han and Kumar (2013) add that these stocks are overpriced, and therefore feature low expected returns. We would add that the same properties, skewness and low returns, characterize individual investors' use of out-of-the-money options.

6. Discussion of broader issues

6.1. Causality

A major finding in this paper is that the impact of technical analysis on returns is concentrated in the subgroup of high derivative rollers. Consider the question of whether technical analysis and high derivative rolling are causally related. To examine this question, we compare two sets of conditional probabilities associated with our sample.

The first set involves the probability of using technical analysis conditional on being a high derivative roller and conditional on being a non-high derivative roller, respectively. The second set involves the probability of being a high derivative roller conditional on using technical analysis and conditional on not using technical analysis, respectively. We then compare both magnitudes of these probabilities and associated likelihood ratios.

The probability of using technical analysis, conditional on being a high derivative roller is 50.4%, whereas the probability of using technical analysis conditional on not being a high derivative roller is 26.5%. The ratio of these two probabilities is 1.9. The probability of being a high derivative roller conditional on using technical analysis is 32.2%, whereas the probability of being a high derivative roller conditional on not using technical analysis is 14.5%. The ratio of these two probabilities is 2.2.

The values of both likelihood ratios indicate that high derivative rolling and technical analysis tend to be clustered in our sample, as the probability of each feature approximately doubles once we condition on the other. Suppose that being a high derivative roller were to be the cause underlying the use of technical analysis, but not vice versa. In this case, the probability of using technical analysis, conditional on being a high derivative roller, would be unity, but the probability of being a high derivative roller, conditional on using technical analysis would be less than unity.

None of the four probability values mentioned above are unity. However, the probability of using technical analysis, conditional on being a high derivative roller is 50.4%, which is 57% higher than the 32.2% probability of being a high derivative roller, conditional on using technical analysis. As a result, we conclude that there is evidence of weak causality from high derivative rolling to technical analysis. In other words, being a high derivative roller inclines individual investors to use technical analysis.

Applying the same line of inquiry leads us to conclude that within the subgroup of high derivative rollers, speculation is a weak causal driver of technical analysis (with a conditional probability of 53.3% and a likelihood ratio of 1.5). However, we do not find evidence of a causality effect with non-high derivative rollers. Nor do we find evidence of a causality relationship between speculation and high derivative rolling.

6.2. Combined effects of technical analysis, speculation, and high derivative rolling

As we noted in the preceding subsection, technical analysis and speculation tend to be clustered within high derivative rollers. In this subsection, we discuss the implications of such clustering on risk-adjusted returns (Carhart's alpha).[34]

To establish a base rate for this discussion, consider the value of Carhart's alpha that is associated with investors in our sample who are not high derivative rollers, do not use technical analysis, and do not have speculation as their primary objective. For this subgroup, the value of Carhart's alpha is −53 basis points per month.

Consider the incremental effect of high derivative rolling, by examining Carhart's alpha for the subgroup of investors who are high derivative rollers, but do not use technical analysis and do not have speculation as their primary objective. The value of Carhart's alpha for this subgroup is −120 basis points, which is 67 basis points lower than the base rate. The incremental effect compared with the base rate is statistically significant ($p = 0.00$, $t = 3.87$).

Next, we assess the incremental impacts associated with speculation and technical analysis on high derivative rollers. To do so, we partition the group into two subgroups, those with speculation as their primary objective and those with some other primary objective. Notice that both groups include investors who use technical analysis. The value of Carhart's alpha for the speculators is −328 basis points, and for the non-speculators it is −152 basis points. The difference between these two groups is statistically significant ($p = 0.04$, $t = 2.12$). Clearly, speculators earn much lower risk-adjusted returns than non-speculators.

[34] In Section 5.5, we noted that for high derivative rollers, technical analysis reduces Carhart's alpha by 130 basis points per month. This figure is an average effect for the high-derivative roller subgroup, and does not take into account the effects associated with control variables such as experience, log portfolio value, and the two turnover variables, all of which feature statistically significant coefficients. However, within high derivative rollers, there is considerable variation in the values of the control variables, especially when we sort the data by technical analysis and speculation. Moreover, we also find additional regime-change effects that we discuss in Appendix A6. This section provides insights about interpreting the 130 basis-point figure, given variations across the different subgroups making up high derivative rollers.

Of particular interest is the incremental impact of technical analysis on the two subgroups of high derivative rollers. For the non-speculators, the incremental effect of technical analysis is −69 basis points. This incremental effect, however, is not statistically significant ($p = 0.11$, $t = 1.63$). However, for the speculators, the incremental effect of technical analysis is −554 basis points.[35] The latter incremental effect is statistically significant ($p = 0.09$, $t = 1.74$).

We conclude that technical analysis is the high octane fuel that, when added to high derivative rolling and the speculative motive, results in abysmal risk-adjusted returns of −656 basis points per month.[36] In contrast, Carhart's alpha for high derivative rollers who use technical analysis but do not report speculation as their primary objective is −189 basis points per month. Although −189 basis points is a substantial figure, it clearly pales in comparison to −656 basis points. The latter difference is statistically significant ($p = 0.00$, $t = 2.92$).

6.3. *High derivative rollers and risk*

One of the most important features that distinguishes high derivative rollers from other investors is risk appetite and associated portfolio risk. The results from Table 8 for the whole sample indicate that risk appetite is positively associated with the standard deviations associated with gross returns and net returns. Separate regressions on high derivative rollers and non-high derivative rollers indicate that the same pattern holds for both subsamples in respect to gross and net returns, but is stronger for high derivative rollers (see Table A6.2 in Appendix A6 for the regression results pertaining to the high derivative roller subsample).

Similar statements apply to data sorted and defined by technical analysis and speculation, where both variables are 0/1 as above. Take any subgroup so defined, and partition it into two, according to whether its members are high derivative rollers or not. We find that in our data, for any subgroup so defined and so partitioned, the high derivative rollers will both have higher risk appetites and higher portfolio risk than their non-high derivative roller counterparts. Here we use standard deviations of net returns to measure portfolio risk.

For non-high derivative rollers, standard deviations of monthly net returns fall in the range 7.1–9.5%. For high derivative rollers, standard deviations fall in the range 12.4–15.3%. Notably, high derivative rollers who use technical analysis and have speculation as their primary objective are associated with the highest standard deviation. Investors who use technical analysis and have speculation as their primary objective are also associated with the largest difference in standard deviations between high derivative rollers and non-high derivative rollers.[37]

6.4. *Regime-change effects associated with high derivative rolling*

Although the return effects associated with technical analysis are concentrated among high derivative rollers (see Section 5.5), many of the other effects discussed in the paper apply to non-high derivative rollers too, and in some cases only to non-high derivative rollers.

For example, the impact of technical analysis on portfolio concentration (HHI) is statistically present only among non-high derivative rollers. We suspect that this is because high derivative rollers hold significantly ($p = 0.00$, $t = -3.63$) more concentrated portfolios (HHI = 31.2%) than non-high derivative rollers (HHI = 27.3%), and as a result, there is less variation available in the data to explain the technical analysis dummy among high derivative rollers.

As for turnover, we find that the impact of technical analysis on turnover for stocks is only significant for non-high derivative rollers. This finding serves to highlight the degree to which derivatives, rather than stocks, is central to trading by high derivative rollers. The impact of technical analysis on turnover for derivatives is significant for both high derivative rollers and non-high derivative rollers, but as one would expect, is stronger for high derivative rollers.

In line with our discussion in Section 3, the effect of technical analysis on the factor loading for momentum is statistically significant for both high derivative rollers and non-high derivative rollers, but is stronger for high derivative rollers.

In respect to risk, one notable difference between high derivative rollers and non-high derivative rollers concerns the ratio of nonsystematic risk to total risk. In contrast to non-high derivative rollers, for high derivative rollers, there is no significant impact of technical analysis or turnover of stocks, and a weaker effect for turnover of derivatives on this ratio.

[35] We also conducted this analysis by reversing the roles of technical analysis and speculation, and found that technical analysis had the larger incremental impact.

[36] We note that among the high derivative rollers, derivatives turnover for the subgroup using technical analysis and having speculation as a primary objective, is between 1.2 and 1.4 times higher than for any other subgroup. Relative to non-high derivative roller subgroups, it is between 18 and 47 times higher. We suggest that these relative comparisons help to explain the abysmal risk-adjusted returns of high derivative rollers who use technical analysis and have speculation as their primary objective. However, we also note that there is so much return variation within this subgroup that the associated regression coefficient, while distinctly negative, is not significant.

[37] The differential risk appetite values and differential return standard deviations described in this paragraph are inversely related. Hence, the high derivative roller impact on return standard deviation is strongest for the subgroup of investors having the smallest risk-appetite differential, which happens to be investors who use technical analysis and have speculation as their primary investment objective. This suggests that the choice of how much risk to bear might be impacted by other variables besides risk appetite, such as excessive optimism, overconfidence, and high aspiration levels.

6.5. Gender

We find that men are more inclined to use technical analysis than women. In our data, the fraction of men using technical analysis is 33%, while the fraction of women using technical analysis is 29%. This difference is significant ($p = 0.01$, $t = 2.60$). In addition, while the fraction of men in our data is 77%, for the investors using technical analysis, the fraction of men is 80%, and for the investors using technical analysis exclusively the fraction is 85%. For high derivative rollers, the fraction of men is 84%, for high derivative rollers using technical analysis, the fraction of men is also 84%, and for high derivative rollers using technical analysis exclusively the fraction is 92%.[38]

To place the results of this subsection into context, we note that high derivative rollers constitute 20% of our sample. Among high derivative rollers, 23% report speculation as their primary objective. Of the speculative high derivative rollers, 53% use technical analysis, and as mentioned above, for those exclusively using technical analysis as a strategy, 92% are men. For the non-speculative high derivative rollers, 50% use technical analysis. However, they earn 468 basis points more per month in risk-adjusted returns than their speculative high derivative rolling counterparts.

7. Conclusion

Since the seminal work of LLS (1974, 1976, 1977, 1978a,b, 1980), which analyzed data from the 1960s, the study of how technical analysis impacts individual investors has received little attention in the finance literature. Yet, the investment landscape has changed dramatically since those times, especially with the advent of online trading through discount brokerage. By analyzing data on Dutch investors during the period 2000–2006 who used an online discount broker, we find that technical analysis impacts the portfolios of individual investors in economically important ways.

To the best of our knowledge, ours is the first paper to isolate the impact of using technical analysis from other factors such as speculation as an investment objective, turnover, concentration, and demographic variables such as gender. Relative to the use of other strategies, we find that technical analysis is associated with greater portfolio concentration, more turnover, less betting on trends, more options trading, a higher ratio of nonsystematic risk to total risk, lower gross and net returns, and lower risk-adjusted returns.

We estimate that for our data, technical analysis costs investors on average approximately 50 basis points per month in raw returns from poor portfolio selection decisions, and 20 basis points from additional transaction costs. Notably, the impact of technical analysis is concentrated among high derivative rollers, where the costs are much higher: 140 basis points in raw returns, and 29 basis points from additional transaction costs.

In terms of both magnitude and statistical significance, the effects of technical analysis are strongly confined to investors who are high derivative rollers. Basically, high derivative rollers who do not use technical analysis earn 56 basis points per month of risk-adjusted return less than investors who are not high derivative rollers, irrespective of whether the latter use technical analysis. Our study shows that additionally technical analysis dramatically accentuates the poor average performance of high derivative rollers by -130 basis points. Notably, high derivative rollers hold riskier portfolios than non-high derivative rollers, and report having larger risk appetites.

Our results add to the literature on technical analysis, by providing empirical evidence to support the remarks in Neely (1997) that technical analysis is not suitable for individual investors, even though it can be suitable for professional investors.

Our results add to the literature documenting that for individual investors, high turnover and concentration are manifestations of excessive optimism and overconfidence (see Barber and Odean, 2000; Glaser and Weber, 2007; Goetzmann and Kumar, 2008; Anderson, 2013). We find strong effects associated with high derivatives turnover, suggesting that excessively optimistic, overconfident investors are much more inclined to use technical analysis than other investors. In this regard, we find evidence of causality from high derivative rolling to technical analysis, with high derivative rollers being almost twice as inclined to use technical analysis than other investors. Half of all high derivative rollers use technical analysis.

Our results add to the literature documenting that individual investors are prone to invest in lottery-like securities that feature high risk and negative risk-adjusted returns (see Kumar, 2009; Han and Kumar, 2013). We find that technical analysis is the high octane gasoline that speculative high derivative rollers use to fuel their lottery-like trading. In this regard, the incremental impact of technical analysis on the risk-adjusted returns to high derivative rollers is 468 basis points per month less for speculators than for non-speculators.

Our results add to the literature about individual investors and price trends, for which there is both an empirical literature (Grinblatt and Keloharju, 2001) and an experimental literature (Andreassen, 1987, 1988). Both provide evidence that for trends based on horizons longer than two days, investors are prone to bet on reversals. However, the experimental literature also suggests that when subjects are provided with information that purportedly explains the cause of the trend, they bet on continuation, not reversal. Our results indicate that investors who use technical analysis bet less on reversals than other investors.

We find that the reported use of technical analysis is greater in our data than in the older LLS data, 32% vs. 27%, suggesting that costly behaviors have increased over time. The proportion of investors who use technical analysis by itself is more than

[38] In addition to gender, Appendix A7 contains a discussion about the connection between the characterization in Anderson (2013) of "high stake" investors and our characterization of investors who report using technical analysis. We also find that men are more inclined than women to use fundamental analysis.

double in our data than in the LLS data, 9% vs. 4%. Most notable is the marked reduction in the number of investors who report using fundamental analysis, with the percentage in our data being less by a factor of roughly two thirds, 20% vs. 65%. The general advice from behavioral finance for individual investors is that they restrict their attempts to beat the market, and instead invest most of their portfolios as if markets were efficient (Shefrin, 2000). Doing so helps them avoid shooting themselves in the foot as a result of falling prey to their own psychological vulnerabilities. Our findings suggest that this advice is apt for individual investors using technical analysis, especially if they are trading options online through a discount broker.

Appendix A.

A.1. *Academic literature on technical analysis*

The academic literature on technical analysis we discuss begins with Allen and Taylor (1990) and Taylor and Allen (1992), who discuss the importance of technical analysis in foreign exchange markets. Brock et al. (1992) study the efficacy of technical trading rules and find that some rules are informative. Neely (1997) briefly surveys the literature on foreign exchange and technical analysis, and suggests that while professional investors might be able to use technical analysis to generate positive abnormal returns, he does not believe that the same comment applies to individual investors. Sullivan et al. (1999) reanalyze the Brock et al. findings, and confirm that data snooping does not negate the original results. Sullivan et al. also report, however, that for the 1987–1996 period, none of the technical rules in Brock et al. provide incremental information. Lo et al. (2000) report that conditioning on the value of certain technical indicators can provide incremental information, but is not necessarily profitable. Neely et al. (2009) discuss the use of technical rules in the foreign-exchange market and report that some technical rules provide incremental information during the 1970s and 1980s, but not thereafter. Consistent with these results, Schulmeister (2009) and Park and Irwin (2007) find that technical trading rules only yield economic profits in U.S. markets until the late 1980s, but not thereafter. Marshall et al. (2010) conduct a test of technical analysis using data from 49 countries, including the Netherlands and the U.S., and conclude that technical analysis performs better in emerging markets than in developed ones. Smith et al. (2013) report that about one-third of actively managed equity and balanced funds use technical analysis, with the latter generating values for alpha and volatility which are generally higher. Menkhoff and Taylor (2007) connect investment strategy to an investor's investment horizon, with technical analysis being associated with a short horizon relative to other strategies.

A.2. *Impact of salient price points on predictions and trades*

De Bondt (1993) studied situations when there are salient lows or highs early in the price series. He finds that non-experts form confidence intervals that tend to be skewed, featuring longer tails in the direction of reversal. Similarly, Mussweiler and Schneller (2003) examine the impact of salient prices in long-horizon histories on price predictions, which they compare to Andreassen's (1988) study of patterns in recent short histories. Mussweiler and Schneller find that a salient past high or low induces predictions of reversal to the salient point. In this regard, we note that the concepts of support and resistance levels used in technical analysis refer to salient highs and lows in price charts. In line with Mussweiler and Schneller (2003), Grinblatt and Keloharju (2001) report that being at a monthly low induces individual investors to buy, whereas being at a monthly high induces individual investors to sell.

A.3. *Survey questions (Translated from Dutch)*

Variable name and survey question	Answer categories
Novice/advanced/very advanced investor	
What type of investor do you consider yourself to be?	*1–A novice investor*
	2–An advanced investor
	3–A very advanced investor
Risk appetite	
What type of investor do you consider yourself to be?	*1–Very Conservative*
	2–Conservative
	3–Defensive
	4–Careful
	5–Offensive
	6–Speculative
	7–Very speculative
Ambition	
How ambitious do you consider yourself to be?	*1–I am not ambitious*
	2–I am a bit ambitious
	3–I am moderately ambitious
	4–I am quite ambitious
	5–I am very ambitious

Variable name and survey question	Answer categories
Investing strategies Which strategies do you use as a basis for your investment decisions (multiple answers possible)?	*1–Technical analysis: I base my investment decisions on technical analysis* *2–Fundamental analysis: I base my investment decisions on fundamental analysis* *3–Professional advice: I base my investment decisions on the professional advice from an investment advisor* *4–Intuition: I base my investment decisions on my personal intuition*
Investment objectives What is the most important investment objective regarding your portfolio at this brokerage firm?	*1–Saving for retirement: being able to stop working at an earlier age* *2–Hobby: interest in the stock market* *3–Building financial buffer: building a financial buffer for future expenses* *4–Speculation: trying to profit from short-term developments on the stock market* *5–Capital growth: achieve a higher expected return than on a savings account*

A.4. : Excerpts from online broker's start-up manual for new clients

The snapshots below are excerpts from the online brokerage firm's start-up manual for new clients. The excerpts explain the differences between fundamental and technical analysis. An English translation from the original text in Dutch is provided for the underlined parts of the excerpts.

2.4.3 Fundamentele analyse

De fundamentele analyse van een fonds vindt u op de overzichtspagina van een fonds onder het tabblad 'fundamentele analyse' of in de navigatiebalk onder 'Analyse'. Fundamentele analyse richt zich op de financiele en economische situatie van een bedrijf. U kunt ondermeer kijken naar gegevens als koers-winstverhoudingen, dividendrendementen en andere waardevolle bedrijfsinformatie.

Fundamental analysis focuses on the financial and economic situation of a company. Amongst other things, one can examine P/E-ratios, dividend yields, and other valuable company information.

2.4.5 Technische analyse (TA)

De technische analyse van een fonds vindt u op de overzichtspagina van een fonds onder het tabblad 'technishe analyse' of in de navigatienalk onder 'Analyse'. Met technische analyse kijkt u naar het verleden, en herkent u patronen in de historische grafiek. Aan de hand hiervan neemt men een standpunt in over de toekomstige koersontwikkeling.Royce Tostrams is een specialist in technische analyse en hij biedt u eenvoudig inzicht in de technische analyse grafiek van een aandeel. In een oogopslag ziet u of een aandeel koopwaardig is volgens de technische analyse. Tostrams maakt dit inzichtelijk door de trends, de steun en weerstand voor u opeen rij te zetten. Tevens geeft Tostrams adviezen over vele (internationale) fondsen en sectoren.

With technical analysis, one observes the past and tries to recognize patterns in a historical graph. Based on this, one takes a stance on the future stock price development [of a company]. . . .In the blink of an eye, one sees whether a fund/stock is worth buying according to its technical analysis . . . showing a fund/stock's trends, support levels, and resistance levels.

A.5. Dataset comparisons

In Table A5.1 below, we provide a summary of our comparison of key descriptive statistics across the datasets used by LLS, Barber and Odean, and the current study.

A.5.1. Comparing LLS data and our data

In addition to dataset comparisons discussed elsewhere in the paper, consider two additional points. The first concerns trading motivated by gambling (speculation) and entertainment (hobby). Investors in the LLS dataset indicate that they regard these objectives as being the least important when making their investment decisions. In contrast, investors in our

Table A5.1
Key Descriptives–LLS vs. Barber–Odean vs. This Study.

	LLS (1980)	Barber–Odean (2000)	Barber–Odean (2002)	This study (2014)
Sample period	1964–1970	1991–1996	1991–1996	2000–2006
Age (mean at time of each study)	57.49	50.60	49.60	49.70
Male account	0.80	0.79	0.86	0.77
Portfolio size (mean in March 2006 Dollars)	682,165	60,227	171,772	60,589
Turnover (mean fraction per year)	0.38	0.76	0.96	2.76
Net returns (mean per year)	0.086	0.164	0.138	−0.021
Net returns minus market returns (mean per year)	0.005	−0.015	−0.037	−0.014

This table compares key descriptive statistics across the datasets of LLS (1978b), Barber–Odean (2000), Barber–Odean (2002), and this study. Numbers for the Barber–Odean (2002) sample refer to their sample of online investors only and are for after switching from phone-based trading to online trading. Variables are defined in Table 1.

dataset rate them as being second in importance.[39] Additionally, compared to investors in the LLS dataset, investors in our dataset give the objective of retirement savings very low importance.

Second, some investors in both datasets have brokerage accounts at other firms. In theory, this might explain some differences between the datasets. For example, one can think of an investor who maintains an account at a full-fee broker, where he uses fundamental analysis, and who also maintains an account at a discount broker, where he uses technical analysis. This behavior could explain why the use of fundamental analysis is so much lower in our dataset than in LLS. The proportion of investors in our dataset who do not maintain other brokerage accounts, however, is high enough that we feel we can rule out this possibility. Moreover, our conclusions do not depend on investors holding their entire portfolio with a single broker.

A.5.2. Comparing Barber–Odean data and our data

As a consistency check, we compare our data for Dutch investors who use a discount broker and trade online to the Barber–Odean data for U.S. investors who use a discount broker. In this regard, investors in our data are similar to those in the Barber–Odean data in terms of gender composition and age. Mean portfolios are also about the same: In 2006 dollars, it is \$60,227 for Barber and Odean (2000) and \$60,589 for our data. The corresponding portfolio for only the investors who switch to online trading in Barber and Odean (2002) is \$171,772.

The investors in our data trade more than the Barber–Odean investors, which is consistent with the fact that our dataset consists of online investors only, who typically trade more actively than offline investors (Barber and Odean, 2001b, 2002; Choi et al., 2002). Annual stock turnover in Barber and Odean (2000) is 0.76; it is 0.96 in Barber–Odean (2002), and 2.76 in our data.[40]

The investors in our dataset underperform the market by 1.4% annually, whereas the Barber–Odean (2000) investors underperform by 1.5%, and the Barber–Odean (2002) investors underperform by 3.7%. The LLS investors outperform by 0.5% annually.

A.5.3. Comparing LLS data and Barber–Odean data

Investors in these two datasets differ with respect to the sizes of their portfolios. In nominal terms, the mean portfolio in the LLS data is \$105,500. In contrast, the mean portfolio in the Barber–Odean (2000) data is \$47,334. This difference is accentuated once inflation is taken into account. In this regard, recall that the two sample periods are different. The LLS sample period is 1964–1970, while the Barber–Odean (2000) sample period is 1991–1996. Adjusting for the change in the Consumer Price Index (CPI) between the end of each of the two sample periods, the mean portfolio size in the LLS data is \$541,498 (measured in 1996 dollars). The mean Barber–Odean portfolio is thus only 8.7% the size of the mean LLS portfolio.[41]

These differences in portfolio size and especially the performance relative to the market, in combination with the choice of broker (discount versus full fee), are consistent with the notion that LLS investors are more sophisticated than their Barber–Odean counterparts. An important point in common is the impact of turnover: Both LLS (1980) and Barber and Odean (2000) point out that because of transaction costs, active investors underperform.

In respect to type of brokerage, Barber and Odean (2000) report a major difference between the performance of investors in their discount brokerage data and investors in the LLS full-fee brokerage data. Barber and Odean indicate that the investors in their data perform poorly, which they attribute to overconfidence. In contrast, LLS (1978a) indicate that their findings “portray an overall picture of quite respectable individual investor security selection acumen” (p. 322). Barber and Odean suggest that one reason for this difference is that the LLS data pertain to full-fee brokers whereas their data involve a discount broker.

Regarding online trading, Barber and Odean (2002) suggest that the ability to trade online exacerbates overconfidence (see also Choi et al., 2002). They point out that during the 1992–1995 period, investors who went online earned superior returns before switching to online trading, but after the switch increased their trading activity, traded more speculatively, and earned inferior returns. Barber and Odean explain their finding as follows: “Several cognitive biases reinforce the overconfidence of online investors. Once online, investors have access to vast quantities of investment data; these data can foster an illusion of knowledge, which increases overconfidence. . .. [O]nline investors generally manage their own stock portfolios and execute trades at the click of a mouse; this fosters an illusion of control, which reinforces overconfidence.” (p. 481).

[39] In rough terms, the portfolio sizes in our sample, segmented by objective, are as follows: capital growth (€65,000), saving for retirement (€50,000), building financial buffer (€45,000), speculating (€35,000), and hobby (€25,000). Notice that although the portfolios of speculators and hobbyists are smaller than those of investors saving for retirement and investing for capital growth, the magnitudes suggest that serious money is at stake. In regard to seriousness, LLS (1980) point out that investors with smaller, more concentrated portfolios involving speculative securities spend six times as many hours managing their portfolios as other investors.

[40] The investors in our data also hold more stocks than the Barber-Odean investors. The mean number of stocks held in Barber-Odean (2000) is 4.3, while in our data it is 6.6. Note, however, that Barber-Odean (2000) only include common stocks when counting the number of different stocks an investor holds, while we also include mutual funds. Barber-Odean (2002) do not mention the number of stocks that the investors in their study hold.

[41] Moreover, the mean Barber-Odean (2000) investor holds far fewer individual stocks than its LLS counterpart (4–5 as opposed to 10–15). Note, however, that Barber-Odean (2000) only include common stocks when counting the number of different stocks an investor holds, while LLS also include other types of securities.

Table A6.1
Returns.

	Gross returns		Net Returns		Carhart's Alpha	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Intercept	−0.090	−1.64	−0.188 ***	−3.15	−0.046	−1.26
Characteristics and traits						
Age (years)	0.000	−0.53	0.000	−0.64	0.000	−0.83
Experience (months)	−0.001 ***	−4.43	0.000 **	−2.42	0.000	0.23
Male account	−0.007	−1.15	−0.007	−1.08	−0.002	−0.50
Novice investor	0.071 *	1.68	0.072	1.56	−0.004	−0.17
Advanced investor	0.056	1.33	0.057	1.25	−0.013	−0.54
Very advanced investor	0.035	0.81	0.036	0.78	−0.007	−0.30
Risk appetite	−0.001	−0.50	−0.002	−0.76	0.000	−0.13
Ambition level	0.003	1.01	0.003	0.91	0.002	0.85
HHI	−0.024 ***	−2.94	−0.029 ***	−3.26	−0.005	−0.79
Log portfolio value (€)	0.011 ***	4.43	0.019 ***	7.42	0.003	1.31
Turnover stocks	0.001	0.22	−0.003	−1.01	−0.005 **	−2.07
Turnover derivatives	0.003	1.31	−0.005 **	−2.45	−0.004	−0.78
Strategies						
Technical analysis	−0.014 **	−2.34	−0.014 **	−2.20	−0.013 ***	−3.10
Fundamental analysis	0.004	0.57	0.004	0.53	0.001	0.20
Professional advice	−0.017 **	−2.07	−0.015	−1.64	−0.011	−1.67 *
Intuition	−0.001	−0.25	−0.002	−0.33	−0.003	−0.75
Objectives						
Saving for retirement	−0.017	−0.86	−0.018	−0.83	0.018	1.24
Hobby	−0.003	−0.20	−0.002	−0.12	0.033 ***	2.88
Building financial buffer	−0.016	−0.88	−0.016	−0.79	0.039 ***	3.17
Speculating	−0.013	−0.78	−0.017	−0.91	0.036 ***	2.92
Capital growth	−0.014	−0.85	−0.014	−0.75	0.034 ***	2.93
Adj. R^2		0.089		0.146		0.171
No of Observations		1100		1100		1100

This table reports cross-sectional regression estimates to explain investors' monthly returns (gross returns, net returns, and risk-adjusted returns (Carhart's alpha)) for high derivative rollers, defined as the quintile of investors associated with the highest derivatives turnover. Variables are defined in Table 1.
* Statistical significance at 10%.
** Statistical significance at 5%.
*** Statistical significance at 1%.

A.5.4. Additional differentiating issues

On most key variables, the investors in our data are similar to those in both the LLS data and the Barber–Odean data. Some general points that need to be identified, however, are differences in national retirement savings programs and changes in technology over time. In respect to savings, the Dutch counterpart to Social Security, for example, offers a much higher ratio of benefits to labor income than does the U.S. Social Security system. This might explain the difference in investors' tendency to directly invest in the stock market to save for retirement. In respect to the use of technical analysis, computer data processing and the Internet have made it easier and cheaper to construct and access technical charts than was the case during the 1960s, when charts were either hand-constructed or purchased from a service.

A.6. Risk and return regressions for high derivative rollers

In this appendix, we present regressions results for the subsample of high derivative rollers, defined as the quintile of investors associated with the highest derivatives turnover.

In the high derivative roller subsample, the coefficient for the variable "speculating" in the regression for Carhart's alpha is statistically significant, but also positive in sign (see Table A6.1 above). The positive sign is at odds with the results from the following sort-based comparison. We conduct a two-way sort of high derivative rollers based on technical analysis and speculation. Consider two subsamples of investors who do not use technical analysis. The first subsample does not have speculation as their primary objective, while the second does. In our data, the second sample features the higher mean value of Carhart's alpha, which is consistent with the sign of the regression coefficient. The difference between the two subgroups is 0.2%, and the two subgroups together comprise 46.7% of high derivative rollers.

Similarly, partition the high derivative rollers who use technical analysis into speculators and non-speculators. The corresponding difference for this group is −4.7%, which implies a strong negative effect associated with speculation, which is at odds with the positive coefficient value mentioned above. Additional "smaller" regressions of Carhart-alpha on just HHI and the turnover variables (untabulated) feature negative coefficients which are much larger in absolute value for the speculators than the non-speculators. This suggests a regime-change effect. Notably, the regression intercept for the speculators is positive, while for the non-speculators it is negative. This regime-change effect appears to express itself in the regression (whose results are displayed in Table A6.2) by impacting the coefficient of the "speculating" dummy variable,

Table A6.2
Risk.

	Gross return Standard Deviation		Net return Standard Deviation		Adj. *R*-Squared Carhart	
	Coeff	*t*-stat	Coeff	*t*-stat	Coeff	*t*-stat
Intercept	.249 ***	3.83	.245 ***	3.87	.087	0.42
Characteristics and traits						
Age (years)	−.001 **	−2.05	−.001 **	−2.10	.001	0.98
Experience (months)	.002 ***	10.24	.002 ***	10.52	.000	−0.35
Male account	−.018 **	−2.49	−.018 **	−2.56	.011	0.47
Novice investor	−.011	−0.23	−.017	−0.35	.160	1.15
Advanced investor	−.027	−0.54	−.030	−0.61	.174	1.28
Very advanced investor	−.001	−0.03	−.005	−0.10	.273 *	1.94
Risk appetite	.007 ***	3.14	.007 ***	2.99	.008	1.08
Ambition level	.000	0.05	.000	0.13	.002	0.13
HHI	.029 ***	3.01	.030 ***	3.13	−.076 **	−2.23
Log portfolio value (€)	−.020 ***	−7.01	−.019 ***	−6.97	.021	1.82 *
Turnover stocks	.007 *	1.85	.006 *	1.74	−.009	−0.71
Turnover derivatives	.014 ***	6.05	.013 ***	5.78	−.046 *	−1.71
Strategies						
Technical analysis	−.009	−1.35	−.007	−1.06	−.028	−1.20
Fundamental analysis	.000	−0.05	−.002	−0.24	.073 ***	2.71
Professional advice	−.006	−0.59	−.004	−0.47	−.025	−0.70
Intuition	.016 **	2.33	.017 **	2.57	−.009	−0.40
Objectives						
Saving for retirement	.006	0.27	.005	0.22	−.093	−1.11
Hobby	−.005	−0.24	−.003	−0.17	.035	0.54
Building financial buffer	−.017	−0.77	−.017	−0.80	−.013	−0.19
Speculating	.010	0.52	.011	0.55	.042	0.60
Capital growth	−.008	−0.39	−.008	−0.41	.024	0.37
Adj. R^2		0.228		0.290		0.188
No of Observations		1100		1100		1100

This table reports cross-sectional regression estimates to explain investors' risk-taking (standard deviation of monthly gross returns, standard deviation of monthly net returns, Adjusted R^2 Carhart's alpha regression) for high derivative rollers, defined as the quintile of investors associated with the highest derivatives turnover. Variables are defined in Table 1.

* Statistical significance at 10%.
** Statistical significance at 5%.
*** Statistical significance at 1%.

whose positive sign reflects the difference in intercept values for the smaller regressions. For that matter, and with one exception, all the coefficients associated with objectives are statistically significant, and share approximately the same values.

In respect to the coefficients, the marginal regime-change effect for the high derivative rollers using technical analysis in respect to speculation and no speculation is about double for turnover, and over triple for HHI. Actual turnover is 30–40% higher for speculators than non-speculators. These effects are consistent with the results from our sort procedure.

A.7. Anderson's characterization of high stake investors

Anderson (2013) provides evidence that stake size predicts turnover for all investors, but is less pronounced for those who are more sophisticated, and that high-stake investors perform less successfully than average investors. He further asserts that individual characteristics which the finance literature has previously used to proxy for excessive optimism and overconfidence (e.g., lower wealth, younger age, being male, less education) are strongly related to stake size, thereby implying that concentration proxies for these biases.

Below, we examine the extent to which in our data investors using technical analysis have less wealth, are younger, and are more likely to be men.[42] Our findings support Anderson's position, and sharpen it to say that technical analysis is a primary vehicle for the expression of these biases through trading. Technical analysis, more than any other strategy we investigate, allows for the strong manifestation of excessive optimism and overconfidence.

Table A7.1 below reports differences in investor characteristics across four investment strategy groups:

1. investors using technical analysis without fundamental analysis;
2. investors using fundamental analysis without technical analysis;
3. investors combining fundamental analysis and technical analysis; and

[42] In Section 6 we discussed our findings about technical analysis and gender. We do not have data on level of education which Anderson (2013) also described as being associated with overconfident behavior.

Table A7.1
Key descriptives across investment strategies.

	Technical analysis, but not fundamental analysis	Fundamental analysis, but not technical analysis	Technical analysis and fundamental analysis	Other strategies	p-value of F-test
Key variables					
Percent of investors (%)	22.83	11.18	8.52	57.47	
Male account	0.80	0.81	0.79	0.75	0.001(5.30)***
HHI (%)	30.39	25.60	25.82	27.84	0.002(4.81)***
Portfolio value (€)	35,893	80,019	62,516	40,793	0.000(17.43)***
Age (in years as of 2006)	49.61	48.74	50.25	49.79	0.199(1.55)
Experience (months)	36.70	43.77	37.82	41.27	0.000(22.74)***
Monthly gross returns	−0.002	0.008	0.006	0.006	0.000(9.591)***
Standard deviation of gross returns	0.094	0.086	0.082	0.083	0.001(5.279)***
Monthly net returns	−0.015	0.003	−0.003	0.000	0.000(22.366)***
Standard deviation of net returns	0.094	0.085	0.082	0.083	0.001(5.503)***
Monthly Carhart's alpha	−0.010	−0.006	−0.006	−0.006	0.006(4.179)***
Adj. R^2 Carhart regression (%)	58.19%	62.83%	59.40%	61.28%	0.002(5.016)***
Percent novice investor (%)	29.06	17.97	14.16	49.12	0.000(151.98)***
Percent advanced investor (%)	61.49	67.81	67.38	46.61	0.000(61.25)***
Percent very advanced investor (%)	9.45	14.22	18.45	4.26	0.000(57.96)***
Percent saving for retirement as primary investment objective (%)	6.18	6.29	6.81	6.69	0.924(.16)
Percent hobby as primary investment objective (%)	28.05	22.35	21.32	26.31	0.005(4.26)***
Percent building financial buffer as primary investment objective (%)	10.08	11.59	11.65	12.71	0.112(1.99)
Percent speculating as primary investment objective (%)	16.83	10.43	19.34	10.61	0.000(16.98)***
Percent capital growth as primary investment objective (%)	36.99	47.35	39.34	40.05	0.000(6.12)***
Percent no investment objective (%)	1.87	1.99	1.54	3.63	0.001(5.24)***

This table compares key descriptive statistics across investors who use each of the following investment strategies: technical analysis, but not fundamental analysis; fundamental analysis, but not technical analysis; technical and fundamental analysis; other strategies. The data are to be interpreted with reference to columns. For example, consider the investors who report using technical analysis, but not fundamental analysis. The percentage so reporting in the data is 22.83%, the fraction who are male is 80%, the percentage who classify themselves as novices is 29.06%, and the percentage who report that saving for retirement is their primary objective is 6.18%. Variables are defined in Table 1. We report the p-value of F-tests to show significant differences, reporting the F-ratio between brackets.

*** Statistical significance at 1%.

4. investors using all other strategies.

In line with the characterization which Anderson (2013) provides for "high stake" investors, Table A7.1 indicates that relative to other investors, those who report using technical analysis without fundamental analysis have more concentrated portfolios (higher HHI) which are also smaller in size.[43] Given our findings about high derivative rollers, we note that HHI for high derivative rollers is 31.2%, whereas HHI for all other investors is 27.3%. The difference is significant ($p = 0.00$, $t = -3.63$). For high derivative rollers using technical analysis, HHI is even higher, 32.2%, although the difference between 32.2% and 31.2% is not statistically significant ($p = 0.33$, $t = -.97$).

We note that the number of option positions for high derivative rollers is 4.4, whereas for all other investors the number of option positions is 1.4. This difference is significant ($p = 0.00$, $t = -12.05$). Within high derivative rollers, the use of technical analysis has no significant impact on the number of option positions.

Reported users of technical analysis without fundamental analysis are the least experienced. Although they are neither the youngest nor are significantly different in age from other investors, we find that the mean age of investors for the subset using technical analysis exclusively is 48.7 years, which is lower than any of the values reported in Table A7.1.

Table A7.1 also indicates that users of technical analysis without fundamental analysis regard themselves as more advanced than other investors, except for investors using fundamental analysis without technical analysis. Notably, users of technical analysis without fundamental analysis are less likely to have capital growth as an objective than any other investment group, are more likely to have speculation as a primary objective than all other groups except for those combining fundamental analysis and technical analysis, and are the most likely to have hobby as a primary investment objective.

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[43] Of course, lower returns associated with the use of technical analysis contributes to smaller portfolios.

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