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Investor attention and portfolio performance: what information does it pay to pay attention to?

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ABSTRACT

We explore a unique dataset on individual investors' online trading accounts to examine the determinants of their attention and its relation to portfolio performance. In particular, we investigate what individual characteristics affect investor attention and what type of information drives investment performance. We find distinct differences in investors' attention and provide evidence that paying attention has a differential impact on performance depending on the type of information. Portfolio monitoring and attention to financial education are positively related to performance, while attention to analytical information is detrimental to performance. Attention to technical analysis is negatively related to the performance of actively trading investors but improves the performance of less frequent traders. Overall, our results provide additional evidence to the suggestion that attention to financial education is the key to investment success.

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1. Introduction

Investors have access to vast amounts of information from various sources. However, as the seminal study of Kahneman (1973) shows that people are restricted in allocating their limited cognitive resources, paying attention to the right information may play an important role in determining investment performance. Hence, it is not surprising that a vast amount of the literature focuses on the effects of investor attention on asset prices. For example, Da, Engelberg, and Gao (2011) and Corwin and Coughenour (2008) find that an increase in investor attention to particular stocks is associated with higher prices and liquidity of those stocks, while Vlastakis and Markellos (2012), Andrei and Hasler (2015) and Da Costa et al. (2013) document that investor attention to stocks also increases their volatility. The majority of these studies investigate the broad market effects of investor attention to financial information while utilizing search engine volumes (for example, Google) as a proxy for investor attention. More recent studies have, however, turned towards the investigation of the effects of investor attention on individual portfolio outcomes. Sicherman et al. (2016) present evidence on how household trading is related to investor attention, while Gargano and Rossi (2018) find that investor attention is associated with better performance. Despite the extensive literature on the effects of investor attention, it still remains mostly unclear what affects investors' allocation of their attention between different types of information and, more importantly, how this allocation of attention is reflected in investment performance.

Besides investors' overall attention, their attention to financial education is another factor that may affect the investment outcomes of individual investors, as more financially educated investors are supposedly able to better understand and process analytical and technical information. Lusardi and Mitchell (2014) define financial literacy as '… people's ability to process economic information and make informed decisions about financial

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planning, wealth accumulation, debt, and pensions.' An interesting question in this regard is whether paying attention to educational information has any impact on investment performance.

In this paper, we aim to extend the previous literature by investigating how investor attention to different types of information, including attention to financial education, affects portfolio performance. We employ an extensive and exclusive dataset of retail investors from the large Swedish bank 'Avanza'. Essentially, Avanza is a fully digital platform for savings and investments, which is accessed by retail customers via a web page. This feature allows us to track the behavior of individual customers once they have accessed the platform. Apart from traditional brokerage services, Avanza also provides its clients with access to financial news and analysis, as well as educational material. This variety of materials enables us to divide investor attention into three primary types of information.

First, Avanza prepares 'Guide pages' for each stock that summarize information on stock prices and dividends, the relevant trading recommendations, and the latest news on companies and other company-related discussions. We refer to the views of these Guide pages as a proxy for investor attention to analytical information. Second, Avanza's customers can also access tools for technical analysis of underlying stocks by clicking on the corresponding links. We extract the number of these clicks to measure investor attention to technical analysis. Third, Avanza provides extensive educational material for its clients, which can be accessed on the so-called 'Avanza Academy' pages. These pages include comprehensible information on various investment concepts such as risk, diversification principles, securities and assets characteristics, and other useful information, supplemented with in-depth explanations and applied examples. We refer to the views of the Avanza Academy pages as a proxy for investor attention to financial education. We interpret investor attention to Academy pages as the use of 'just-in-time' financial education (see Fernandes, Lynch, and Netemeyer 2014). Finally, we track the number of days on which a customer accesses the platform as a proxy for general attention to investment portfolios.

By employing these novel measures, we examine whether investor attention to portfolio information, analytical information, technical analysis, and financial education affects portfolio performance. Our dataset also includes information on investor demographics and portfolio turnover, allowing us to analyze the determinants of investor attention. Website analytics and portfolio performance data recorded in 2017 are available for more than 500,000 individual investors.

Following the recent evidence of Gargano and Rossi (2018), we hypothesize that individual investor performance improves with higher attention to the overall portfolio and analytical information. Furthermore, we test two additional hypotheses that are novel to the literature. First, we hypothesize that individual investor performance improves with higher attention to financial education. This hypothesis is partially in line with the previous evidence suggesting that a higher level of financial literacy leads to better investment outcomes (Von Gaudecker 2015; Bianchi 2018), and that learning and education can help to overcome the disposition effect (see e.g. Vaarmets, Liivamägi, and Talsepp 2019). Second, following the existing evidence from Hoffmann and Shefrin (2014), we also hypothesize that higher attention to technical analysis is detrimental to investor performance.

Our results demonstrate that investor attention has a differential impact on investment performance depending on the type of information. We find that performance deteriorates with higher attention to analytical information, while general attention to portfolio information and attention to financial education is associated with better performance. These findings hold in a variety of robustness tests and confirm the results of Gargano and Rossi (2018), who also find that increased portfolio attention is associated with better investment performance. We extend these findings and show that investors who pay more attention to financial education perform better. Our results on investor attention to technical analysis are partly in line with the previous literature, which documents that using technical analysis is associated with poorer investment performance (Hoffmann and Shefrin 2014). However, we find this relationship to be significant only in the case of active investors, while investor attention to technical analysis appears to be associated with better performance for less active investors.

By focusing on investor attention to different types of information, our study contributes to two different strands of the literature: first, our study adds to the research on financial education and investment outcomes. Prior studies suggest potential transition channels from traders' financial education and literacy to investment performance. For example, Vaarmets, Liivamägi, and Talsepp (2019) show that learning and education may help to overcome the disposition effect, which is the tendency of investors to sell winners too early and ride losers for too long (see e.g. Shefrin and Statman 1985). Von Gaudecker (2015) provides empirical evidence that households who are more financially literate or who rely on professional advice for their trading decisions achieve better investment outcomes. Closely related to our study, Bianchi (2018) combines survey data with investors' portfolio choices and finds that more literate households earn higher risk-adjusted returns. Collectively, these empirical findings suggest that better financial literacy achieved through financial education may influence the investment performance of individual investors. However, none of these studies distinguishes between attention to analytical information and attention to financial education. In this paper, we are able to examine the importance of investor attention to educational information besides attention to analytical information by accessing the data on the volume of views of the corresponding web pages. Our variable for attention to financial education does not directly measure actual financial literacy or self-perception of financial literacy as considered in Anderson, Baker, and Robinson (2017). Instead, it measures people's attempt to become more financially literate, which is a new perspective in the literature.

Second, the unique dataset enables us to identify investor attention to technical analysis, which is very well-recognized among retail investors and receives coverage in the media. It is a compelling method for investors to improve their investment performance, as there is evidence that simple technical trading rules can be profitable (e.g. Brock, Lakonishok, and LeBaron 1992; Szakmary, Shen, and Sharma 2012; Szakmary and Lancaster 2015; Chiarella and Ladley 2016). However, the attractiveness of technical analysis is challenged by Hoffmann and Shefrin (2014). By matching the data on transaction records and survey responses on whether the investor uses technical analysis, they document that using technical analysis may be detrimental to investment performance. While we contribute to this stream of the literature by empirically examining the effect of investor attention to technical analysis on portfolio performance, there are two crucial differences between our study and the study by Hoffmann and Shefrin (2014). First, instead of using investors' self-perceived usage of technical analysis from survey responses, we use records of actual views of pages with technical analysis. And second, our measure of attention to technical analysis is not dichotomous, which enables us to quantify the intensity of attention to technical analysis.

The remainder of the paper is organized as follows. We develop the hypotheses of our study in Section 2 and present the data, measures of investor attention, and methodology in Section 3. We continue with the empirical results and a variety of robustness tests in Section 4 and conclude the paper in Section 5.

2. Hypotheses development

Since the study by Kahneman (1973), attention has been regarded as a scarce cognitive resource. Theoretical models of investor attention (e.g. Van Nieuwerburgh and Veldkamp 2010; Kacperczyk, Van Nieuwerburgh, and Veldkamp 2016) predict that investors with limited attention should benefit from paying more attention. Following this strand of literature, Gargano and Rossi (2018) consider attention as one of the main determinants of investment performance. They find that investors who pay more attention have better-performing portfolios and execute better trades, implying that they are able to acquire valuable information while spending time in their investment accounts.

The recent evidence suggests that paying more attention can be beneficial also from a behavioral perspective. Dierick et al. (2019), for example, argue that attention may reflect one's commitment, which presumably weakens the severity of cognitive dissonance. They provide evidence that less attentive investors exhibit trading patterns of the disposition effect, which is investors' tendency to hold on to losing positions and to give up winning. This effect seems to have a considerable impact on investment performance, given the findings of Odean (1998) who documents that the disposition effect leads to lower returns. Taken together, previous studies indicate that more attentive investors perform better. Therefore, we expect that general investor attention to portfolio information, as measured by the number of days the investor is logged into the account during the year, should be associated with better performance:

H1: Individual investor performance improves with higher attention to the portfolio.

While our first hypothesis concerns overall attention to investment portfolios, investors may pay attention to different types of information while being logged into their accounts. Gargano and Rossi (2018), for instance, differentiate between investor attention to different sources of information based on the time spent on 'Research' and 'Balances and Positions' pages of the trading platform. They find that both types of attention are associated with better performance. Building on this evidence, we also hypothesize that higher investor attention to analytical information is associated with better investment performance. However, given that the analytical information may have different content with respect to Research pages used in Gargano and Rossi (2018), this hypothesis is rather speculative as investors may misperceive some of this information (e.g. blindly follow analyst recommendations). Therefore, if investors are not able to extract useful trading signals from analytical information or if they misinterpret this information, we would observe unaffected or even poorer investment performance of the traders who pay more attention to such information. On the other hand, if these investors are capable of benefiting from analytical information, they should demonstrate superior portfolio performance. Hence, our second hypothesis is:

H2: Individual investor performance improves with higher attention to analytical information.

Previous literature also suggests that financially more literate investors demonstrate better diversification outcomes (e.g. Abreu and Mendes 2010; Von Gaudecker 2015). Given that a properly diversified portfolio is expected to improve risk-adjusted investment performance, it would be natural to expect that investors with higher levels of financial literacy perform better. This expectation is confirmed by the existing empirical evidence (see e.g. Bianchi 2018). However, the attention to financial education does not directly measure the actual level of financial literacy or self-perception of this literacy as considered, for example, in Anderson, Baker, and Robinson (2017). Instead, we observe investor attention to educational material, which is aimed to increase the financial literacy of an investor. Vaarmets, Liivamägi, and Talsepp (2019), for instance, show that learning and education can help to overcome the disposition effect, which may positively affect the overall portfolio performance. Moreover, Fernandes, Lynch, and Netemeyer (2014) provide evidence that financial education tied to a particular decision (or 'just-in-time' education) better conveys content information than previously obtained education, as the effects of financial education tend to decay over time. Thus, investor attention to 'just-in-time' financial education should matter even for investors who have previously received corresponding education. We refer to this evidence and interpret investor attention to the educational material as the use of 'just-in-time' financial education related to a particular investment decision. Following this narrative, we hypothesize that investors who pay more attention to 'just-in-time' financial education should be able to better apply their knowledge and consequently achieve better portfolio performance:

H3: Individual investor performance improves with higher attention to financial education.

Brock, Lakonishok, and LeBaron (1992) and a stream of more recent research (e.g. Szakmary, Shen, and Sharma 2012; Szakmary and Lancaster 2015; Chiarella and Ladley 2016) suggest that simple technical trading rules can be profitable. However, this view has been challenged in several studies. Sullivan et al. (1999), for instance, evaluate simple technical trading rules adjusted for the effect of the data snooping bias and show that the rules used in Brock, Lakonishok, and LeBaron (1992) did not outperform in an out-of-sample experiment. More recently, Park and Irwin (2007) review the evidence on the profitability of technical analysis and point out that even though the majority of studies in the field document positive effect, most of them are subject to various problems in testing procedures. Furthermore, Bajgrowicz and Scaillet (2012) re-examine the historical success of technical trading rules on daily prices of the Dow Jones Industrial Average index from 1987 to 2011 and show that the prominence of technical analysis is seriously challenged by transaction costs and the ability to select ex-ante future best performing rules.

Despite this contradictory evidence from the existing literature on the profitability of technical analysis, it is still a very eminent investment approach. Hoffmann and Shefrin (2014) particularly focus on investors, who self-report the use of technical analysis, and evaluate their performance. While they admit that the use of technical analysis could lead to a surge in gross returns due to increased trading on momentum, they argue that the marginal impact on individual investor performance is negative due to higher turnover, greater portfolio concentration, and a lower ratio of nonsystematic risk to total risk. They also document that investors who rely on technical analysis are subject to many adverse patterns in their investment behavior and as the result earn lower returns, more probable to speculate, and have more concentrated portfolios. Following this evidence, we expect that attention to technical analysis is also detrimental to individual investor performance as traders who access technical analysis tools are likely to perceive them as relevant for their investment decisions:

H4: Investor attention to technical analysis is detrimental to investment performance.

3. Data, attention measures, and methodology

3.1. Data

In this study, we use the data from the Swedish Internet-based bank 'Avanza'[1] for the year 2017. The data contain information on investors' portfolio annual performance, their demographics, and the attention they pay to different types of information available on the bank's webpages. In particular, we observe the number of days investors are logged into their accounts and specific web pages that they are browsing within the bank's resources. The data on portfolio performance consist of four portfolio characteristics based on investor trading activity in 2017: portfolio turnover, annual return, standard deviation, and Sharpe ratio.[2] The annual return is based on the net asset value (NAV) at the beginning and end of the year. The standard deviation is annualized and calculated based on daily returns. The returns are calculated excluding any deposits or withdrawals during the year, but including any incurred dividends. Thus, the annual return is a net-of-fees time-weighted total return. The Sharpe ratio is calculated using the annual return and annualized standard deviation and assuming zero risk-free rate. We make this assumption because short-term market interest rates in Sweden were negative during the whole of 2017. For example, the Stibor 3-month rate was −0.591% on December 30, 2016. Since retail investors at Avanza are not offered deposit accounts with interest rates below zero, we use zero as the risk-free rate.[3]

We use the values of portfolio turnover, annual return, standard deviation, and Sharpe ratio to filter out any investors who may bring potential bias to our further analysis. In particular, we remove any investors without available Sharpe ratios, returns, or standard deviations, as well as those with extreme values of Sharpe ratios[4] and/or turnover ratios. This selection leaves us with a total of 5,11,641 individual investors.[5]

Investors' demographic data include information on gender, age, and account tenure. The account tenure variable is the number of days an investor has had an account with Avanza as of December 31, 2017. We consider account tenure as a proxy for investor experience. It is a relevant control variable that, as several studies show, can explain investment outcomes. For example, Nicolosi, Peng, and Zhu (2009) show that more investment experience is associated with better performance. Feng and Seasholes (2005) and Da Costa et al. (2013) also find that more experienced investors are less affected by the disposition effect, which is the tendency of investors to hold onto their losing stocks more than their winning stocks.

3.2. Measures of investor attention

The main variables of interest in our study are four different measures of investor attention. We construct these measures based on investors' activity on the brokerage account website. The first measure is *Logins*, which is a proxy for overall investor attention to portfolio information and calculated as the natural logarithm of the number of days the investor was logged into the investment account in 2017.[6] This variable is similar to the investor attention variable used in Sicherman et al. (2016) and Gargano and Rossi (2018), who find that higher levels of attention are in general associated with better investment performance. Similarly, we also expect that higher levels of the overall investor attention would imply that investors monitor their positions more closely and thus are less likely to miss lucrative investment opportunities.

The second measure is *GuideViews*, which is the natural logarithm of the number of Avanza Guide page views and is a proxy for investor attention to analytical information. Gargano and Rossi (2018) employ a somewhat similar attention variable but they use attention to Research pages, which are characterized by detailed analyst reports and balance sheet information of the underlying companies. The content of our Guide pages differs from the Research pages in Gargano and Rossi (2018) to the extent that it summarizes different stock-specific information such as dividend dates, recommendations from different banks, as well as buying and selling statistics. Hence, we postulate that the information on the Research pages in Gargano and Rossi (2018) is more detailed and the use of that information demands more time and effort. Figure 1 presents an example of the Avanza Guide page for Ericsson B shares.

The third measure is *AcademyViews*, which is a proxy for attention to financial education and calculated as the natural logarithm of the number of Avanza Academy page views by an investor. The Avanza Academy pages serve as a one-stop source of financial knowledge. In addition to the description of various financial instruments and ratios, they contain information on investment concepts and diversification principles, personal finance and taxation, pension and budget planning. More importantly, the educational material on the Academy pages is not a simple combination of various definitions taken from a textbook but rather an explanation of the mechanisms of how different financial ratios work with detailed examples tailored specifically for retail traders, who may not have sufficient knowledge of financial terms. Figure 2 illustrates a sample page from the Avanza Academy, which explains the meaning and the use of the price-to-sales ratio. Academy pages also include a search function, which makes the navigation through the educational material fairly simple, allowing an investor to reach needed content effortlessly. Presumably, investors rely on the Avanza Academy as a place where they can find answers to specific questions on investments, personal finance, and taxation. To illustrate how the Avanza Academy pages differ from Guide pages, consider the Avanza Academy page as in Figure 2, which shows the definition and calculation techniques of the price-to-sales ratio, whereas the Guide page as in Figure 1 shows the actual value of the price-to-sales ratio of the underlying firm. Therefore, we postulate that attention to financial education captures investors' willingness to understand what does financial information mean, how does it work, and how it can be used in trading decisions, which is hardly can be considered less important than knowing the actual level of the financial ratios reported on the Guide pages. To the best of our knowledge, such a measure of attention to financial education is totally new in the literature.

The fourth measure is *TAviews*, which is the natural logarithm of the number of technical analysis views on the Avanza Guide pages. Although the technical analysis tools are available through the Guide pages, they are not visible by default. To activate the tools the investor must click on the graph in two separate places. The procedure needs to be repeated each time investor accesses the Guide pages. Hence, we argue that the number of clicks on technical analysis tools captures investor attention to technical information, which is distinct from analytical information available on the Guide pages. While we acknowledge that attention to technical analysis does not necessarily imply that investors base their decisions on the technical analysis rules, we argue that due to the specific activation procedure of the technical analysis tools, investors, who use these tools, are likely to perceive them as relevant for their investment decisions. This variable for investor attention to technical analysis is also completely novel to the literature.

The set of our attention measures has a hierarchical order. First, an investor must log into the account before being able to view the Academy or Guide pages. Second, the investor must view a Guide page before it is possible to view technical analysis since the technical analysis tools are available through the Guide pages. Thus, *Logins* represent investor attention to broader information than *AcademyViews* and *GuideViews,* while *GuideViews* represent investor attention to broader information than *TAviews*. We also account for this hierarchy in the empirical analysis. Furthermore, similar to Gargano and Rossi (2018), our paper deals with only endogenous attention (the investor's voluntary decision to pay attention) and does not consider exogenous attention (some triggers that interrupt investors' endogenous attention and channel their attention to a different matter). Such distinction between endogenous and exogenous attention may be important as the recent evidence suggests that attention triggers may stimulate individual investors' risk-taking (see e.g. Arnold, Pelster, and Subrahmanyam (2020) who examine push notifications as the source of exogenous attention). Nevertheless, the scope of our study, due to data limitations, is endogenous investor attention.

3.3. Descriptive statistics

Table 1 presents the sample's descriptive statistics. The statistics for the portfolio turnover variable show that at least 25% of the investors did not trade in 2017. Thus, a relatively large fraction of the sample investors is rather inactive. This investor inertia is, however, much more moderate than in Dahlquist, Martinez, and Söderlind

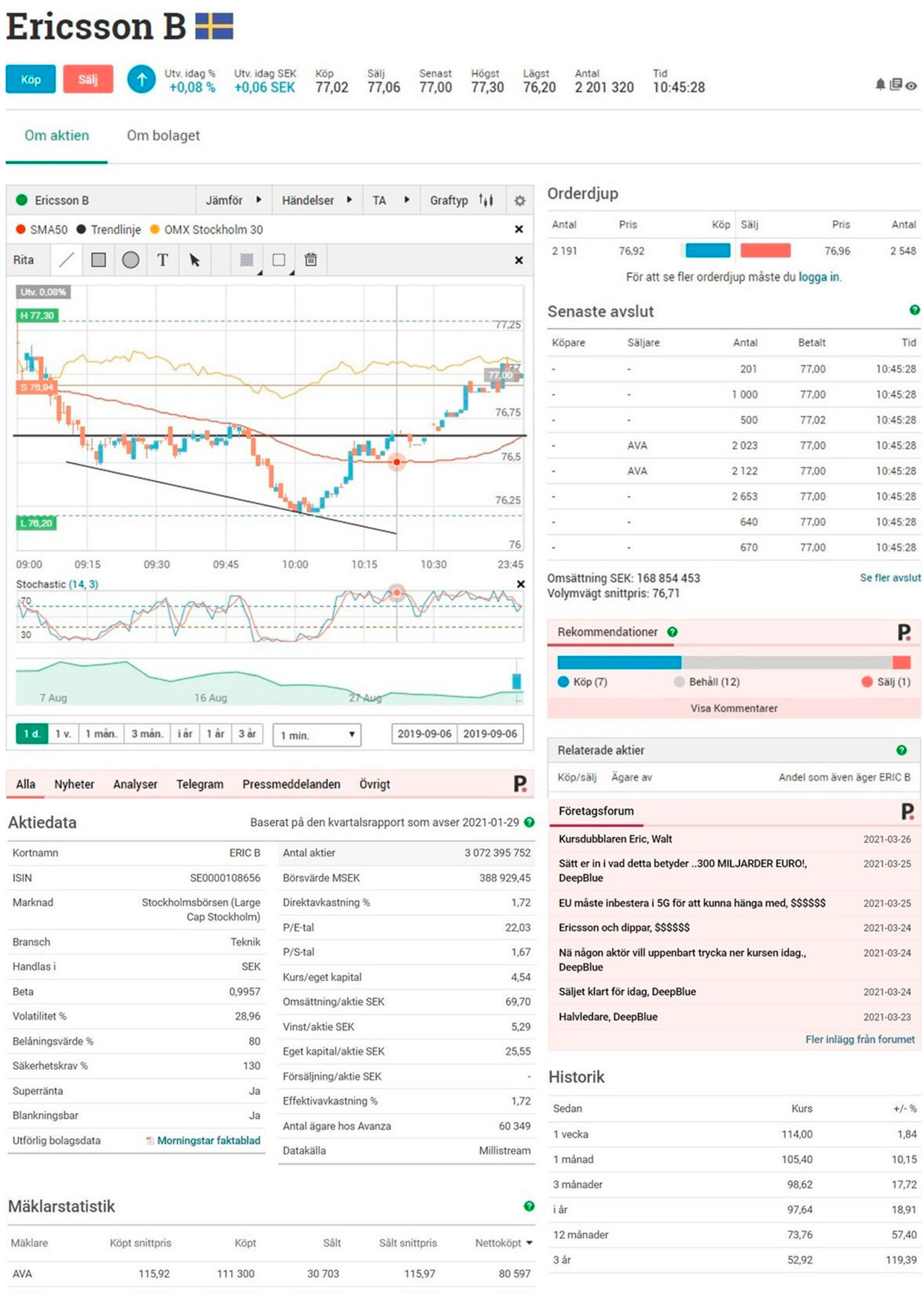

Figure 1. Sample of a Guide page and Technical analysis page. This figure presents an example of a Guide page together with its technical analysis functionality. The Guide page includes, among other things, information on stock prices, a limit order book, the latest news about the company, dividend payments and analyst recommendations.

Stocks

How does the P/S-ratio work?

The P/S-ratio shows the relationship between stock price and a company's sales or revenue. Many investors use it as one of many ratios to get a general overview of a stock before deciding to buy or sell. Here, you can find more information on the other ratios that can be used alongside the P/S ratio [*hyperlink*].

How is the P/S-ratio calculated?

To calculate the P/S-ratio, the stock price is divided by the revenue per share

$$\frac{\textbf{Stock price}}{\textbf{Revenue/Share}} = \textbf{P/S ratio}$$

What does the P/S-ratio show?

This ratio shows how highly the market is valuing a company's revenue. If a company has a high P/S-ratio, it may mean two things. On one hand, it could be that the company's stock price is high in relation to its revenue, which may mean that it is highly priced. On the other hand, it may mean that the market has strong expectations about that company and believes that its revenue is going to increase in the future. When the market is anticipating higher revenues, stock prices tend to increase along with the ratio.

Contrariwise, a low P/S-ratio may indicate that the stock price has a low price in relation to the revenue per share, or due to the market is expecting that the company's revenue will fall.

Example

The delivery company Bokmalen AB has a market value of 500 mill SEK and annual revenue of 300 mill SEK. To calculate the company's P/S-ratio, we divide the market value of the company by its annual revenue.

$$\frac{\mathbf{500}}{\mathbf{300}} = \mathbf{1.67}$$

Bokmalen has a P/S-ratio of 1.67, which in this example is higher than of its competitors from the industry, which is on average about 1.3. Such a high value of the ratio that Bokmalen has means that the market values each SEK in sales higher than of its competitors. The difference may be due to several reasons, for example, that they make more money or the belief that the sales of the company will increase in the future.

Figure 2. Sample of an Academy page. This figure presents an example of an Avanza Academy page, which explains the P/S ratio. It shows how the measure is calculated and how investors can use it in their decision making. The original page is available only in Swedish. The text below is an unofficial translation.

(2017), who study Swedish pension plan investors and find that 69% of non-coordinated investors in their sample made no changes during the 2000–2010 period. On the other hand, the statistics of the same variables show that at least 25% of the investors have a turnover ratio of more than 316%[7] and were logged into their accounts on average on 195 out of 365 days in 2017. This distribution implies that our sample is very heterogeneous in terms of individual investors' trading activity.

Table 1 also shows that the median sample investor earned 9% p.a. in returns, obtaining a Sharpe ratio of 1.00. The investors are in general relatively experienced and mature as the median account tenure and age are 2 033 days (more than 5.5 years) and 41 years, respectively.[8] It should be noted that the median account tenure

Table 1. Descriptive statistics.

Panel A. Descriptive statistics for investors and portfolio characteristics

	Mean	StDev	Min	25th Percentile	Median	75th Percentile	Max
Age (years)	43.37	16.80	1.00	31.00	41.00	55.00	107.00
Account Tenure (days)	2,540.48	1,849.33	394.00	951.00	2,033.00	3,750.00	6,659.00
Portfolio Turnover	32,054.15	4,229,733.55	0.00	0.00	61.00	316.00	1,745,576,600
Gender	0.70	0.46	0.00	0.00	1.00	1.00	1.00
Sharpe Ratio	0.77	1.06	−1.73	−0.04	1.00	1.57	3.98
Return	0.05	0.29	−1.00	−0.00	0.09	0.14	18.86
Standard Deviation	0.19	0.29	0.00	0.08	0.10	0.20	20.29
Logins	103.99	108.74	0.00	9.00	56.00	195.00	362.00

Panel B. Descriptive statistics for information source views

	% of Sample	Mean	StDev	Min	25th Percentile	Median	75th Percentile	Max
AcademyViews	24.18%	5.40	10.76	1	1	2	6	741
GuideViews	34.72%	1,002.62	2,953.75	13	42	147	679	182,270
TAviews	6.76%	175.33	1,549.79	1	2	7	33	163,774

Note: This table presents the descriptive statistics of this study. The test variables *Return*, *Standard Deviation* and *Sharpe ratio* are annual and denoted in decimals. *Logins* is the number of days the investor was logged into the investment account in 2017. *AcademyViews* is the number of Avanza Academy page views by the investor. *GuideViews* is the number of Avanza Guide page views. *TAviews* is the number of technical analysis views on the Avanza Guide pages. Panel B denotes the page view variables and also shows the percentage of investment accounts viewing the pages. Age is the investor's age in years and *Gender* is a dummy variable for the investor's gender (male = 1). The sample includes 511,641 investors.

and age in our sample are significantly lower than in the sample of Gargano and Rossi (2018), where they are 7.52 and 51 years, respectively.

Panel B in Table 1 presents the descriptive statistics for page views indicating attention allocation. During 2017, at least one-third of all of the investors under consideration visited the Guide pages, with the median number of views being 146 pages. The visits to the Avanza Academy were more moderate; only 24.18% of the investors viewed on average 5.4 pages. The least attention was allocated to technical analysis – only 6.76% of the investors actually used the technical analysis tool on the Guide pages, with a median of 7 visits. While some investors possess more financial knowledge before investing with a brokerage, these results indicate that retail investors pay little attention to financial education compared to analytical information.

3.4. Methodology

We begin our empirical analysis by examining the determinants of investor attention to various types of information to gauge the relationship between investor characteristics and investor attention. This relationship, if there is any, would allow us to take into consideration any systematic correlations between attention allocation and individual investor characteristics. For example, experienced investors may rely more on technical or analytical information, while younger traders may prefer educational information. We analyze these differences with the following cross-sectional regression model:

$$Attention_i = \alpha_i + \beta_i \times Demographic_i + \gamma_i \times Activity_i + \varepsilon_i, \tag{1}$$

where the dependent variable *Attention* is one of our four attention variables for *(i)* portfolio information *(Logins)*, *(ii)* financial education *(AcademyViews)*, *(iii)* analytical information *(GuideViews)*, or *(iv)* technical analysis *(TAviews)*. *Demographic* includes the natural logarithm of investor age *(Age)* and a dummy variable for the investors' gender (male = 1) *(Gender)*. *Activity* includes the natural logarithms of portfolio turnover *(Turnover)* and account tenure *(AccountTenure)* for an investor *i*. The purpose of the analysis of Equation (1) is to explore what investor demographic and activity characteristics are associated with investor attention.

We proceed with our empirical analysis by testing the hypotheses of our study on whether investor performance is associated with attention to different types of information by estimating the following cross-sectional regression model:

$$PerformanceMeasure_i = \alpha_i + \beta_i \times Demographic_i + \gamma_i \times Activity_i + \lambda_i \times Attention_i + \varepsilon_i \quad (2)$$

where the dependent variable *PerformanceMeasure* is either the Sharpe ratio, annualized standard deviation of returns, or annual return for an investor *i*. *Demographic* and *Activity* are the same variables as in Equation (1), while *Attention* is the attention behavior variables for *Logins, AcademyViews, GuideViews,* and *TAviews*. In all of our regression models, we use White heteroscedasticity-consistent standard errors.[9]

4. Results

4.1. Determinants of investor attention

We begin our analysis by dividing all of the sample investors based on their consumption of particular types of information and comparing their average investment performance measures across the users and non-users of this information in a simple difference in the means test. Table 2 presents the results of these univariate tests for attention behavior. Panel A shows that investors who pay more attention to financial education achieve higher returns and better overall performance in terms of the Sharpe ratio. For instance, investors who view at least one page of the Avanza Academy earn on average 1.2% more in annual returns. It is noteworthy that while investors who view the Academy pages have higher returns, they do not appear to take more risk. It is possible that as attention to financial education increases, diversification becomes an established part of the investment process, thus enabling higher returns relative to risk.

Investors who pay more attention to technical analysis and analytical information, in turn, appear to achieve poorer performance, higher risk, and lower returns. For example, investors who view Guide pages receive on average 2.1% less in annual returns compared to those who do not pay any attention to the Guide pages, while investors who use technical analysis earn on average 0.29% less than non-users of technical analysis. These univariate tests provide support to our hypotheses on the positive effect of higher attention to educational information on individual investor performance (H3) and the detrimental effect from higher attention to technical information (H4). However, we do not observe any support to our hypothesis on the positive effect of higher attention to analytical information (H2), since the users of Guide pages on average seem to underperform relative to non-users.

Panel B in Table 2 depicts the demographic differences and experiences of users of various types of information. Thus, viewers of the Academy and Guide pages are marginally older male investors with shorter account tenures. Interestingly, users of Technical analysis tools seem to be younger males with longer account tenures. Panel C in Table 2 shows that *Logins* is significantly higher for those who use the Avanza Academy, Guide pages, and technical analysis tools.[10] This feature is expected, as investors need to log into their accounts before they can access further web pages within the brokerage domain.

Table 3 presents the regression analysis estimates of Equation (1) with the variables of investor attention to portfolio information, financial education, analytical information, and technical analysis as the dependent variables. Different values of the adjusted R^2 suggest that investor characteristics explain the variability in the portfolio information *(Logins)* and analytical information *(GuideViews)* variables better than the variability in the financial education *(AcademyViews)* and technical analysis *(TAviews)* attention variables. It is noteworthy that the adjusted R^2 is the highest in explaining *Logins* (37.3%) and the lowest in explaining *TAviews* (4.6%).

Regarding the results in Table 3, *Age* seems to have a differential impact on different measures of investor attention. In particular, the impact of *Age* on *TAviews* is negative and statistically significant at the 1% level, while the impact of *Age* on *Logins*, *AcademyViews,* and *GuideViews* is positive and statistically significant at the 1% level. These results suggest that older investors pay more attention to portfolio information, financial education, and analytical information, but they are less likely to use technical analysis. An intuitive explanation for this result is that older investors are potentially seeking to fill the gaps or refresh their knowledge so they pay more attention to 'just-in-time' financial education. These results extend the prior literature, which shows that older investors are less financially literate (e.g. Finke, Howe, and Houston 2016).

Table 2. Univariate tests.

Panel A.

	Users				Non-users				Diff in mean		
	N. of investors	Return	StDev	Sharpe ratio	N. of investors	Return	StDev	Sharpe ratio	Return	StDev	Sharpe ratio
AcademyViews	123,699	0.058	0.188	0.788	387,942	0.046	0.189	0.771	0.012***	−0.001	0.017***
									(12.93)	(−1.36)	(4.96)
GuideViews	177,618	0.035	0.221	0.612	334,023	0.056	0.172	0.861	−0.021***	0.048***	−0.250***
									(−23.48)	(55.46)	(−79.19)
TAviews	34,601	0.022	0.243	0.538	477,040	0.051	0.185	0.792	−0.029***	0.058***	−0.254***
									(−14.09)	(30.06)	(−40.83)

Panel B.

	Users			Non-users			Diff in mean		
	Gender	Age	Account Tenure	Gender	Age	Account Tenure	Gender	Age	Account Tenure
AcademyViews	0.768	43.988	2,284.027	0.675	43.166	2,622.255	0.094***	0.822***	−338.227***
							(66.02)	(15.16)	(−56.91)
GuideViews	0.799	44.030	2,478.721	0.643	43.011	2,573.323	0.156***	1.019***	−94.603***
							(123.72)	(20.96)	(−17.33)
TAviews	0.881	41.408	2,544.184	0.684	43.507	2,640.213	0.197***	−2.099***	3.971
							(105.65)	(−24.93)	(0.37)

Panel C.

	Users		Non-users		Diff in mean	
	Portfolio Turnover	Logins	Portfolio Turnover	Logins	Portfolio Turnover	Logins
AcademyViews	37,294.034	164.80	30,383.362	84.597	6,910.673	80.203***
					(0.60)	(232.41)
GuideViews	43,255.519	164.180	26,097.778	71.980	17,157.741	92.201***
					(1.27)	(308.31)
TAviews	44,678.123	208.040	31,138.498	96.513	13,539.625	111.527***
					(0.81)	(201.74)

Note: This table presents the analysis of the difference in means between users and non-users of information using Welch's test statistic. The test variables are return, standard deviation, Sharpe ratio, Gender, Age, Account tenure, Portfolio turnover and Logins. The values in parentheses are *t*-statistics, whereas *,** and *** refer to statistical significance at the 10%, 5% and 1% levels with the H0 hypothesis that there is no difference in means between the 'Users' and 'Non-Users' groups, respectively. See Table 1 for a definition of the variables. The sample includes 511,641 investors.

Table 3. Determinants of investor attention.

	Logins	AcademyViews	GuideViews	TAviews
Gender	0.669***	0.007***	0.330***	0.064***
	(144.69)	(3.66)	(51.04)	(34.85)
Age	0.632***	0.029***	0.066***	−0.054***
	(129.24)	(15.19)	(10.44)	(−27.57)
AccountTenure	−0.249***	−0.063***	0.095***	0.015***
	(−97.20)	(−49.61)	(22.18)	(10.60)
Turnover	0.319***	0.013***	0.139***	0.023***
	(418.54)	(34.59)	(102.81)	(53.91)
Logins		0.109***	0.558***	0.062***
		(184.70)	(270.74)	(101.33)
Intercept	1.574***	0.267***	−1.878***	−0.088***
	(71.42)	(25.66)	(−53.11)	(−7.72)
Adj. R^2	37.30%	10.40%	24.80%	4.60%
N. Obs.	511,641	511,641	511,641	511,641

Note: This table presents the estimates of the ordinary least squares (OLS) analysis of the determinants of investor attention using the following model:

$$Attention_i = \alpha_i + \beta_i \times Demographic_i + \gamma_i \times Activity_i + \varepsilon_i,$$

where the dependent variable *Attention* is one of our four attention allocation variables: *Logins, AcademyViews, GuideViews* or *TAviews*. *Logins* is the natural logarithm of the number of days the investor was logged into the investment account in 2017. *AcademyViews* is the natural logarithm of the number of Avanza Academy page views. *GuideViews* is the natural logarithm of the number of Avanza Guide page views. *TAviews* is the natural logarithm of the number of technical analysis views on the Avanza Guide pages. *Demographic* includes the natural logarithm of investor age and a dummy variable for the investor's gender (male = 1). *Activity* includes the natural logarithms of portfolio turnover and account tenure for an investor *i*. The standard errors are White heteroscedasticity consistent. *,** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively. The t-statistics are in parentheses. The sample includes 511,641 individual investors.

AccountTenure, in turn, has a negative impact on *AcademyViews*, suggesting that more experienced investors demand less information on financial education. Moreover, *AccountTenure* also has a negative impact on *Logins*, suggesting that more experienced investors monitor their trading accounts less frequently. This finding is in line with the rational inattention hypothesis (see Sims 2003), which argues that attention is costly. Thus, more experienced investors may better understand the costs of paying attention and consequently, pay less attention.

The results in Table 3 for *Gender* show that males pay more attention regardless of the type of information. This finding is consistent with the extensive evidence, suggesting that men are more financially engaged than women and appear to be more active in searching for financial information (e.g. Lusardi, Mitchell, and Curto 2010; Lusardi and Mitchell 2009; Lusardi and Tufano 2009). It is also notable that there is a positive relation between *Gender* and *TAviews*, which is in line with Hoffmann and Shefrin (2014), who find that male investors use technical analysis more than female investors.

We also observe a positive and highly statistically significant effect of *Turnover* on all of our attention measures, implying that more active investors consume more information, regardless of the source. However, this finding should be interpreted with caution, as *Turnover* is endogenous to our attention measures, especially to *Logins*. While we acknowledge this endogeneity concern as a limitation of our study, we ascertain that the rest of our results are not driven by this problem. In particular, we re-estimate Equation (1) without *Turnover* and confirm that the results reported in Table 3 remain the same with only minor differences.[11]

Furthermore, we check whether the prior portfolio performance of an investor has any impact on investor attention allocation by re-estimating our regression specification with an additional control variable – lagged by one-year performance measures. In these estimations, reported in Table A1 in the Online Appendix, we observe that prior portfolio performance is relevant for investors' attention. While the relationship between

Table 4. Attention and investor performance.

	Sharpe ratio			Return			StDev		
Gender	−0.188***	−0.213***	−0.195***	−0.019***	−0.025***	−0.022***	0.056***	0.062***	0.058***
	(−60.49)	(−66.88)	(−61.48)	(−24.91)	(−31.58)	(−28.79)	(74.39)	(78.97)	(74.11)
Age	0.037***	0.014***	0.014***	0.003***	−0.002***	−0.003***	−0.009***	−0.003***	−0.003***
	(11.78)	(4.44)	(4.21)	(4.30)	(−2.85)	(−3.38)	(−11.82)	(−4.43)	(−4.36)
AccountTenure	0.080***	0.089***	0.104***	0.015***	0.017***	0.019***	−0.025***	−0.027***	−0.030***
	(42.75)	(47.01)	(55.07)	(28.59)	(32.02)	(35.91)	(−48.06)	(−51.27)	(−57.46)
Turnover	−0.055***	−0.067***	−0.061***	−0.007***	−0.010***	−0.009***	0.011***	0.013***	0.012***
	(−112.91)	(−113.59)	(−103.48)	(−46.35)	(−54.77)	(−50.44)	(54.73)	(56.04)	(50.35)
Logins		0.036***	0.051***		0.008***	0.010***		−0.008***	−0.012***
		(36.37)	(49.62)		(33.24)	(35.92)		(−28.65)	(−39.05)
AcademyViews			0.153***			0.024***			−0.033***
			(67.60)			(37.24)			(−52.00)
GuideViews			−0.057***			−0.007***			0.013***
			(−79.48)			(−28.77)			(56.73)
TAviews			−0.002			−0.003***			−0.001
			(−1.07)			(−4.25)			(−0.97)
Intercept	0.357***	0.301***	0.152***	−0.039***	−0.052***	−0.071***	0.330***	0.343***	0.376***
	(22.30)	(18.67)	(9.47)	(−8.99)	(−11.96)	(−16.36)	(77.19)	(79.79)	(87.15)
Adj. R^2	4.1%	4.4%	6.0%	0.9%	1.1%	1.5%	3.1%	3.2%	4.3%
N. Obs.	511,641	511,641	511,641	511,641	511,641	511,641	511,641	511,641	511,641

Note: This table presents the estimates of the ordinary least squares (OLS) analysis of the determinants of the Sharpe ratio, annualized standard deviation of returns and annual return of an investor using the following model:

$$PerformanceMeasure_i = \alpha_i + \beta_i \times Demographic_i + \gamma_i \times Activity_i + \lambda_i \times Attention_i + \varepsilon_i,$$

where the dependent variable *PerformanceMeasure* is either the Sharpe ratio, annualized standard deviation of returns or annual return for an investor *i*. *Demographic* includes the natural logarithm of investor age and a dummy variable for the investor's gender (male = 1). *Activity* includes the natural logarithms of portfolio turnover and account tenure for an investor *i*. *Attention* is the attention behavior variables for *Logins, AcademyViews, GuideViews* and *TAviews*. *Logins* is the natural logarithm of the number of days the investor was logged into the investment account in 2017. *AcademyViews* is the natural logarithm of the number of Avanza Academy page views. *GuideViews* is the natural logarithm of the number of Avanza Guide page views. *TAviews* is the natural logarithm of the number of technical analysis views on the Avanza Guide pages. The standard errors are White heteroscedasticity consistent. *,** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively. The t-statistics are in parentheses. The sample includes 511,641 individual investors.

overall investor attention (*Logins*) and past portfolio performance is positive, it seems that poorer prior performance results in increased investor attention to educational (*AcademyViews*) and analytical (*GuideViews*) information. The result that overall investor attention is lower after a poor past portfolio performance is in line with the previous evidence on the ostrich effect (see Karlsson, Loewenstein, and Seppi 2009; Sicherman et al. 2016), suggesting that investors pay less attention to the market after a poor performance.

Overall, the analysis of the determinants of investor attention indicates that there is substantial heterogeneity in attention across different investors, which needs to be accounted for in analyzing the relationship between attention and investment performance.

4.2. Attention and investment performance

Next, we turn to the analyses of our main hypotheses and examine how attention to different types of information affects investor performance. Table 4 presents the estimates of Equation (2) with the Sharpe ratio, return, and standard deviation as the dependent variables. On comparing our results for the portfolio attention variable (*Logins)* with the measure of total attention spent on the brokerage website from Gargano and Rossi (2018), we find consistent evidence that more frequent portfolio monitoring is associated with better investment performance. Specifically, statistically significant coefficients for *Logins* show that portfolio attention is associated with a higher Sharpe ratio and returns, and lower standard deviations. These results are in line with our first hypothesis and they support the notion that investors may acquire useful information while they are logged into their accounts.

Following, Gargano and Rossi (2018) who document that paying attention to research information is positively related to portfolio performance, we also hypothesize that *individual investor performance improves with higher attention to analytical information.* Contrary to our hypothesis, we find that attention to analytical information, measured by the number of views of the Guide pages, has a negative and statistically significant coefficient in explaining the Sharpe ratio of individual investors. However, it should be noted that the Research pages in Gargano and Rossi (2018) are different from the Guide pages in our study. While the Research pages are characterized by detailed analyst reports and balance sheet information from the underlying companies, which may be less relevant for unsophisticated investors, our Guide pages provide more stock-specific essential information such as dividend dates and yields. Therefore, we postulate that analytical information contained on Guide pages is different from research information and has an opposite effect on investment performance.

Turning to the third hypothesis of our study that *individual investor performance improves with higher investor attention to financial education,* the results in Table 4 provide strong support for this hypothesis. The coefficient for *AcademyViews* in explaining the Sharpe ratio is positive and statistically significant, indicating that more attention to financial education is associated with better investment performance. The magnitude of the corresponding coefficient is 0.153, which is an economically sizable effect as one standard deviation increase in investor attention to educational information leads to about 0.11 increase in Sharpe ratio (the standard deviation of logged *AcademyViews* in our sample is 0.727 with average views of 1.31 pages). Such an increase is quite large given that the Sharpe ratio of an average investor in our sample is 0.77. The results in the case of standard deviation and returns also suggest that the more attention investors pay to financial education, the higher the returns and the lower the standard deviation. A potential reason for these results could be that gaining financial knowledge helps investors to invest in instruments with higher expected returns. Having said that, the result for higher returns can be explained by the findings of Bianchi (2018), in that more literate households earn higher returns by holding riskier assets when the expected returns are higher. In addition, by looking at the riskiness of portfolios, we observe that investors who pay more attention to financial education could also be better at diversifying their holdings, which also leads to a higher Sharpe ratio via the denominator of the ratio – standard deviation of returns. This conclusion is in line with the findings of Abreu and Mendes (2010) and Von Gaudecker (2015).

The results in Table 4 are also interesting with respect to the prior literature on technical analysis. In a related study, Hoffmann and Shefrin (2014) find that technical analysis use by individual investors is associated with poorer investment performance. Our results in Table 4 on the fourth hypothesis that *investor attention to technical analysis is detrimental to investor performance* are only partially in line with the study of Hoffmann and Shefrin (2014). We find that more attention to technical analysis is associated with significantly lower returns, but the relationship between attention to technical analysis and the Sharpe ratio is not significant. Furthermore, the results on *Age* and *Gender* are consistent with the evidence from Barber and Odean (2001) and Davydov et al. (2017), in that older investors and women take fewer risks and perform better. The results on *Turnover* are consistent with the evidence by Barber and Odean (2000) and Anderson (2007) who show that high turnover is detrimental to performance. In addition, we find a positive and statistically significant coefficient for *AccountTenure* in explaining the Sharpe ratio, confirming the finding of Nicolosi, Peng, and Zhu (2009) that more investment experience is associated with better performance.

4.3. Attention and investment performance: the role of heterogeneity across investors

The results reported so far may potentially be driven by a certain group of active or inactive investors. To ensure the robustness of our analysis, we re-estimate Equation (2) by four turnover categories: (1) zero portfolio turnover (no trading); (2) portfolio turnover is more than zero but less than or equal to its 33rd percentile (infrequent trading); (3) portfolio turnover is over its 33rd percentile but less than or equal to its 66th percentile (regular trading); (4) portfolio turnover is over its 66th percentile (frequent trading). Table 5 presents these estimations.[12] Interestingly, we observe that inactive traders with zero portfolio turnover (Category 1) experience similar effects on their performance from the overall attention and attention to analytical and educational information as more active traders in categories 2 and 3. This finding implies that passive investors also benefit from paying more attention. Indeed, the individual's choice not to trade can also be considered as an investment

Table 5. Analysis of investor performance by portfolio turnover.

	Category 1: No trading			Category 2: Infrequent trading			Category 3: Regular trading			Category 4: Frequent trading		
	Sharpe ratio	Return	StDev	Sharpe ratio	Return	StDev	Sharpe ratio	Return	StDev	Sharpe ratio	Return	StDev
Gender	−0.219***	−0.024***	0.053***	−0.111***	−0.010***	0.044***	−0.176***	−0.023***	0.059***	−0.204***	−0.030***	0.075***
	(−47.96)	(−22.44)	(45.72)	(−16.03)	(−6.16)	(36.54)	(−23.29)	(−12.78)	(37.85)	(−25.13)	(−13.38)	(27.36)
Age	−0.077***	−0.009***	0.008***	0.048***	0.001	−0.003**	0.106***	0.008***	−0.016***	0.128***	0.008***	−0.037***
	(−19.16)	(−10.90)	(8.24)	(6.46)	(0.54)	(−2.28)	(12.40)	(3.54)	(−7.73)	(13.55)	(3.04)	(−12.17)
AccountTenure	0.018***	0.018***	−0.025***	0.163***	0.014***	−0.034***	0.154***	0.020***	−0.030***	0.114***	0.018***	−0.031***
	(5.69)	(22.04)	(−30.43)	(39.57)	(12.52)	(−40.85)	(36.97)	(17.63)	(−31.37)	(26.95)	(12.71)	(−19.67)
Logins	0.068***	0.004***	−0.014***	0.057***	0.010***	−0.006***	0.058***	0.017***	−0.006***	−0.026***	0.004***	0.007***
	(46.96)	(11.39)	(−35.27)	(24.54)	(16.69)	(−12.65)	(19.93)	(22.83)	(−7.91)	(−8.29)	(4.71)	(5.76)
AcademyViews	0.138***	0.020***	−0.030***	0.156***	0.025***	−0.025***	0.143***	0.023***	−0.025***	0.162***	0.030***	−0.045***
	(30.50)	(18.72)	(−23.06)	(30.98)	(19.82)	(−27.61)	(33.43)	(20.30)	(−29.57)	(38.73)	(20.26)	(−29.47)
GuideViews	−0.121***	−0.016***	0.026***	−0.043***	−0.007***	0.009***	−0.039***	−0.005***	0.008***	−0.059***	−0.010***	0.017***
	(−57.07)	(−20.25)	(39.41)	(−29.43)	(−16.78)	(29.85)	(−28.85)	(−12.80)	(26.63)	(−45.78)	(−18.72)	(30.25)
TAviews	0.006	−0.001	−0.006	0.011**	0.000	−0.004***	0.014***	0.001	−0.006***	−0.015***	−0.004***	−0.000
	(0.67)	(−0.32)	(−1.42)	(2.01)	(0.10)	(−4.41)	(3.57)	(0.63)	(−8.47)	(−4.94)	(−3.59)	(−0.31)
Intercept	1.166***	−0.027***	0.311***	−0.778***	−0.068***	0.430***	−0.996***	−0.191***	0.447***	−0.402***	−0.138***	0.498***
	(45.35)	(−4.19)	(47.25)	(−22.03)	(−7.59)	(66.31)	(−26.97)	(−19.49)	(49.67)	(−10.54)	(−11.23)	(36.44)
Adj. R^2	4.6%	1.3%	3.1%	3.3%	0.8%	3.7%	3.4%	1.2%	2.9%	4.6%	0.9%	2.9%
N. Obs.	177,616	177,616	177,616	111,401	111,401	111,401	111,448	111,448	111,448	111,176	111,176	111,176

Note: This table presents the estimates of the ordinary least squares (OLS) analysis of the determinants of the Sharpe ratio, annualized standard deviation of returns and annual return of an investor by portfolio turnover categories using the following model:

$$PerformanceMeasure_i = \alpha_i + \beta_i \times Demographic_i + \gamma_i \times Activity_i + \lambda_i \times Attention_i + \varepsilon_i,$$

where the dependent variable *PerformanceMeasure* is either the Sharpe ratio, annualized standard deviation of returns or annual return for an investor *i*. *Demographic* includes the natural logarithm of investor age and a dummy variable for the investor's gender (male = 1). *Activity* includes the natural logarithm of account tenure for an investor *i*. *Attention* is the attention behavior variables for *Logins, AcademyViews, GuideViews* and *TAviews*. *Logins* is the natural logarithm of the number of days the investor was logged into the investment account in 2017. *AcademyViews* is the natural logarithm of the number of Avanza Academy page views. *GuideViews* is the natural logarithm of the number of Avanza Guide page views. *TAviews* is the natural logarithm of the number of technical analysis views on the Avanza Guide pages. The portfolio turnover categories are: (1) no portfolio turnover; (2) portfolio turnover is more than zero but less than or equal to its 33rd percentile; (3) portfolio turnover is over its 33rd percentile but less than or equal to its 66th percentile; and (4) portfolio turnover is over its 66th percentile. The standard errors are White heteroscedasticity consistent. *,** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively. The t-statistics are in parentheses. The sample includes 511,641 individual investors.

decision, which may be framed by the information that the individual investor consumes while browsing the website of the brokerage. For example, after reading about the negative role of emotions and impulse trading in portfolio performance on Avanza Academy pages, an investor may refrain from trading. Alternatively, after browsing through analytical information, an investor may choose not to close but hold a position, which meant to be closed.

While the rest of the results are qualitatively similar to those reported in Table 4, there is a notable difference in explaining the Sharpe ratios with respect to attention to technical analysis. The coefficient for *TAviews* in these models is only negative and statistically significant for frequent traders (whose portfolio turnover is over the 66th percentile). This finding provides important evidence with respect to our fourth hypothesis and the prior findings of Hoffmann and Shefrin (2014), suggesting that technical analysis is only associated with poorer performance when it is used by traders who trade frequently (Category 4). Furthermore, it is striking that the coefficients for *TAviews* for infrequent and regular traders (Categories 2 and 3) are positive and statistically significant.

Our finding that attention to technical analysis by frequent traders is associated with poorer performance can be related to the evidence of Barber and Odean (2000), who show that overconfidence is associated with higher levels of trading activity. Thus, one potential explanation for this finding is that frequent traders, who are overconfident, may combine more of their own judgment with technical analysis information, which leads to excessive trading and poorer investment decision. Another potential explanation for this finding could be that retail investors who trade more incur implicit and explicit trading costs, leading to lower returns. On the other hand, frequent trading could be an indication of weaker discipline, so frequent traders may fail to establish their trading on the signals from the technical trading rule. This finding also agrees with reported differences in the performance of different types of Commodity Trading Advisors (CTAs) that short-term CTAs, who by definition trade more frequently, earn lower returns than other CTAs (see e.g. Lundström and Peltomäki 2015).

Regarding the analysis of the standard deviation, the coefficient for *TAviews* is negative and statistically significant for investor groups with infrequent and regular trading activity (Categories 2 and 3). This result, which only applies to these investor groups, implies that using technical analysis is associated with less risk if used by investors who do not trade excessively. These investors may be able to successfully reduce their portfolio risk by using technical analysis. Moreover, the effect of decreased risk seems to translate to higher Sharpe ratios. These are important insights related to the Hoffmann and Shefrin (2014) study and our hypothesis that investor attention to technical analysis is detrimental to investment performance.

To check whether our results are driven by different levels of investor experience, we re-estimate Equation (2) using short, medium, and long account tenure categories. We categorize investor experience as (1) if *AccountTenure* is more than zero but less than or equal to its 33rd percentile (short tenure); (2) *AccountTenure* is over its 33rd percentile but less than or equal to its 66th percentile (medium tenure); (3) *AccountTenure* is over its 66th percentile (long tenure). Table 6 presents the estimation results of this analysis. It is noteworthy that the explanatory power of the model decreases with account tenure. For example, the explanatory power (adjusted R^2) for Sharpe ratios is 7.4% in the case of short account tenure, while it is 3.9% in the case of long account tenure. One explanation for this result could be that investors' individual experience becomes a more dominant driver of their investment behavior and success after they gain more investment experience. Nevertheless, it is interesting that the results on how *Logins*, *AcademyViews,* and *GuideViews* explain the risk and performance variables are not qualitatively altered by investor experience. This finding suggests that the effects of investor attention on portfolio performance are independent of investor experience.

Nevertheless, the results for *TAviews* are not uniform across the different levels of account tenure. Most notably, the coefficient for *TAviews* in explaining the Sharpe ratio is statistically significant and positive for investors with short account tenure, but it is statistically significant and negative for investors with long account tenure. These results suggest that less experienced investors benefit from paying more attention to technical analysis, while more experienced investors perform more poorly when they pay more attention to technical analysis. The other coefficients for *TAviews* suggest that investors with medium and long account tenure earn lower returns and investors with short account tenure take risks when they pay more attention to technical analysis. Thus, the mixed evidence on the relationship between investor attention to technical analysis and the Sharpe ratio could be explained by less experienced investors using technical analysis for risk management.

Table 6. Analysis of investor performance by trading account tenure.

	Category 1: Short tenure			Category 2: Medium tenure			Category 3: Long tenure		
	Sharpe ratio	Return	StDev	Sharpe ratio	Return	StDev	Sharpe ratio	Return	StDev
Gender	−0.213***	−0.032***	0.077***	−0.191***	−0.020***	0.054***	−0.153***	−0.012***	0.036***
	(−38.04)	(−21.19)	(53.34)	(−35.77)	(−15.89)	(42.87)	(−28.28)	(−10.27)	(27.23)
Age	0.054***	0.003**	−0.006***	0.053***	−0.001	−0.007***	−0.071***	−0.008***	−0.007***
	(9.88)	(2.40)	(−4.27)	(10.23)	(−0.48)	(−5.80)	(−11.69)	(−6.03)	(−5.30)
Turnover	−0.084***	−0.011***	0.015***	−0.053***	−0.008***	0.010***	−0.044***	−0.008***	0.010***
	(−80.91)	(−32.80)	(36.00)	(−52.72)	(−26.86)	(26.53)	(−43.11)	(−28.15)	(23.75)
Logins	0.053***	0.016***	−0.014***	0.043***	0.009***	−0.012***	0.051***	0.006***	−0.008***
	(25.64)	(26.73)	(−22.73)	(23.99)	(18.28)	(−23.35)	(31.33)	(17.14)	(−18.34)
AcademyViews	0.151***	0.025***	−0.035***	0.150***	0.022***	−0.029***	0.164***	0.025***	−0.031***
	(42.42)	(21.44)	(−36.40)	(38.55)	(20.69)	(−25.42)	(36.86)	(21.98)	(−26.65)
GuideViews	−0.046***	−0.005***	0.011***	−0.064***	−0.008***	0.014***	−0.059***	−0.007***	0.012***
	(−36.01)	(−11.20)	(27.01)	(−52.00)	(−19.06)	(37.62)	(−48.02)	(−19.14)	(32.27)
TAviews	0.009**	−0.000	−0.002**	−0.006	−0.005***	−0.000	−0.012***	−0.004***	0.001
	(2.52)	(−0.27)	(−2.26)	(−1.57)	(−4.49)	(−0.32)	(−3.16)	(−3.51)	(0.88)
Intercept	0.739***	0.022***	0.182***	0.851***	0.073***	0.157***	1.264***	0.113***	0.152***
	(35.93)	(4.25)	(35.43)	(44.47)	(17.57)	(38.31)	(54.69)	(22.15)	(28.96)
Adj. R^2	7.4%	1.5%	4.7%	5.8%	1.4%	3.9%	3.9%	1.3%	2.8%
N. Obs.	170,889	170,889	170,889	170,225	170,225	170,225	170,527	170,527	170,527

Note: This table presents the estimates of the ordinary least squares (OLS) analysis of the determinants of the Sharpe ratio, annualized standard deviation of returns and annual return of an investor by account tenure categories using the following model:

$$PerformanceMeasure_i = \alpha_i + \beta_i \times Demographic_i + \gamma_i \times Activity_i + \lambda_i \times Attention_i + \varepsilon_i,$$

where the dependent variable *PerformanceMeasure* is either the Sharpe ratio, annualized standard deviation of returns or annual return for an investor *i*. *Demographic* includes the natural logarithm of investor age and a dummy variable for the investor's gender (male = 1). *Activity* includes the natural logarithm of portfolio turnover for an investor *i*. *Attention* is the attention behavior variables for *Logins, AcademyViews, GuideViews* and *TAviews*. *Logins* is the natural logarithm of the number of days the investor was logged into the investment account in 2017. *AcademyViews* is the natural logarithm of the number of Avanza Academy page views. *GuideViews* is the natural logarithm of the number of Avanza Guide page views. *TAviews* is the natural logarithm of the number of technical analysis views on the Avanza Guide pages. The account tenure categories are: (1) AccountTenure is more than zero but less than or equal to its 33rd percentile; (2) AccountTenure is over its 33rd percentile but less than or equal to its 66th percentile; (3) AccountTenure is over its 66th percentile. The standard errors are White heteroscedasticity consistent. *,** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively. The t-statistics are in parentheses. The sample includes 511,641 individual investors.

To check further whether investment performance is affected by the amount of attention paid to financial education, we re-estimate Equation (2) in a subsample based on the intensity of *AcademyViews*. We divide all of the investors into four categories: (1) with zero views of educational information (no use); (2) views below the 33rd percentile but above zero (infrequent use); (3) between the 33rd and 66th percentiles (moderate use); and (4) over the 66th percentile (frequent use). These categories have a natural interpretation, as the first subsample includes investors who pay no attention to financial education, while the other three subsamples proxy for low, moderate, and high attention, respectively. These results are reported in Table 7.

Revisiting the role of demographic characteristics in investment performance, the insignificant coefficient for *Gender* with annual returns as the dependent variable in Category 4 indicates that the difference in annual returns between male and female investors disappears in the sample with high levels of attention to financial education. On the other hand, the coefficients for standard deviation remain positive and statistically significant across all of the subsamples, implying that males hold significantly riskier portfolios. Despite the negative and significant coefficients for the Sharpe ratios in all of the subsamples, we observe a consistent decline in the magnitude of these coefficients for investors who pay different levels of attention to financial education. These results suggest that attention to financial education could play a role in mitigating previously documented gender differences (e.g. Charness and Gneezy 2012; Barber and Odean 2001; Davydov et al. 2017) in investment performance and/or risk-taking.

The effect of age, in turn, becomes more pronounced with attention to financial education. For investors with zero views of the Avanza Academy pages, the estimated coefficients for *Age* in explaining returns and Sharpe

Table 7. Analysis of investor performance by Avanza Academy page views.

	Category 1: No use			Category 2: Infrequent use			Category 3: Moderate use			Category 4: Frequent use		
	Sharpe ratio	Return	StDev	Sharpe ratio	Return	StDev	Sharpe ratio	Return	StDev	Sharpe ratio	Return	StDev
Gender	−0.216***	−0.026***	0.061***	−0.122***	−0.011***	0.050***	−0.100***	−0.008**	0.045***	−0.065***	−0.001	0.041***
	(−60.76)	(−29.82)	(66.61)	(−12.59)	(−4.71)	(25.25)	(−6.14)	(−2.04)	(14.74)	(−5.16)	(−0.45)	(14.31)
Age	−0.013***	−0.005***	0.001	0.148***	0.014***	−0.023***	0.171***	0.012**	−0.024***	0.219***	0.022***	−0.033***
	(−3.85)	(−6.50)	(0.96)	(12.60)	(4.57)	(−8.35)	(8.60)	(2.24)	(−4.91)	(14.48)	(5.67)	(−8.35)
Turnover	−0.060***	−0.008***	0.011***	−0.059***	−0.010***	0.014***	−0.063***	−0.012***	0.017***	−0.063***	−0.010***	0.013***
	(−88.30)	(−41.39)	(42.59)	(−36.08)	(−20.34)	(21.51)	(−22.87)	(−13.54)	(14.14)	(−28.17)	(−14.17)	(10.44)
Logins	0.045***	0.008***	−0.011***	0.105***	0.021***	−0.019***	0.118***	0.022***	−0.019***	0.137***	0.024***	−0.019***
	(40.12)	(28.96)	(−32.45)	(24.96)	(18.83)	(−17.44)	(15.66)	(9.09)	(−10.41)	(21.20)	(14.88)	(−10.51)
AccountTenure	0.106***	0.022***	−0.032***	0.094***	0.012***	−0.025***	0.102***	0.013***	−0.022***	0.068***	0.003*	−0.019***
	(48.64)	(35.44)	(−52.52)	(16.98)	(7.56)	(−16.87)	(11.18)	(4.44)	(−8.90)	(9.73)	(1.67)	(−10.41)
GuideViews	−0.058***	−0.008***	0.013***	−0.078***	−0.010***	0.017***	−0.073***	−0.007***	0.014***	−0.067***	−0.005***	0.012***
	(−62.87)	(−23.88)	(44.37)	(−43.56)	(−17.30)	(32.39)	(−23.76)	(−6.41)	(17.26)	(−26.86)	(−6.84)	(11.95)
TAviews	−0.012***	−0.007***	−0.000	0.003	−0.002	−0.003***	0.003	−0.003**	0.000	0.003	−0.001	−0.001
	(−3.02)	(−5.70)	(−0.23)	(0.81)	(−1.20)	(−2.69)	(0.44)	(−1.97)	(0.22)	(0.92)	(−1.01)	(−1.01)
Intercept	0.264***	−0.075***	0.374***	−0.309***	−0.095***	0.388***	−0.486***	−0.093***	0.361***	−0.475***	−0.078***	0.382***
	(14.52)	(−15.28)	(75.87)	(−6.03)	(−6.53)	(28.27)	(−5.69)	(−3.93)	(17.29)	(−7.22)	(−4.40)	(19.49)
Adj. R^2	5.9%	1.6%	4.0%	8.1%	1.9%	6.6%	7.5%	1.8%	6.6%	6.7%	1.3%	3.6%
N. Obs.	387,942	387,942	387,942	62,200	62,200	62,200	23,342	23,342	23,342	38,157	38,157	38,157

Note: This table presents the estimates of the ordinary least squares (OLS) analysis of the determinants of the Sharpe ratio, annualized standard deviation of returns and annual return of an investor by Avanza Academy page views using the following model:

$$PerformanceMeasure_i = \alpha_i + \beta_i \times Demographic_i + \gamma_i \times Activity_i + \lambda_i \times Attention_i + \varepsilon_i,$$

where the dependent variable *PerformanceMeasure* is either the Sharpe ratio, annualized standard deviation of returns or annual return for an investor *i*. *Demographic* includes the natural logarithm of investor age and a dummy variable for the investor's gender (male = 1). *Activity* includes the natural logarithms of portfolio turnover and account tenure for an investor *i*. *Attention* is the attention behavior variables for *Logins, GuideViews* and *TAviews*. *Logins* is the natural logarithm of the number of days the investor was logged into the investment account in 2017. *GuideViews* is the natural logarithm of the number of Avanza Guide page views. *TAviews* is the natural logarithm of the number of technical analysis views on the Avanza Guide pages. The four categories of Avanza Academy page views are: (1) with zero views of educational information; (2) views below the 33rd percentile but above zero; (3) between the 33rd and 66th percentiles; and (4) above the 66th percentile. The standard errors are White heteroscedasticity consistent. *,** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively. The t-statistics are in parentheses. The sample includes 511,641 individual investors.

ratios appear to be negative and statistically significant, but positive and statistically insignificant in explaining standard deviation. However, these relationships are vice versa for investors who pay more attention to financial education, increasing in magnitude along with increased intensity for this kind of attention. These findings suggest that older investors who pay no attention to financial education perform worse than investors who are more attentive to educational information.

We do not find any additional differences in the effects of *Logins* and *GuideViews* on performance in investors who pay attention to financial education. However, we do observe that the effect of *TAviews* on the Sharpe ratio is conditional on the use of the Avanza Academy. The negative effect of technical analysis on the Sharpe ratio is only statistically significant for investors who pay no attention to educational information. This result suggests that investors who do not pay attention to financial education may be less knowledgeable and poorer users of more sophisticated information, such as technical analysis.

4.4. Attention and investment performance: the role of past performance and previous attention

Given that our data are cross-sectional and do not allow for within-investor analysis, one may argue that the prior portfolio performance of an individual investor may have a significant impact on investor attention and consequently on current performance. While we do not have access to the investor attention allocation measures for prior periods, we obtain records of investors' performance characteristics (Sharpe ratios, returns, and standard deviation of returns) from 2016[13] and re-estimate all our regression specifications with an additional control variable – lagged by one-year performance measures. We tabulate these results in Table 8.

As can be noted from Columns 1–3, lagged performance measures do not affect our made earlier conclusions. We still observe a positive and significant effect of overall attention to the portfolio (*Logins*) on investment performance stemming from both sides: higher returns and lower standard deviation. The opposite relation holds for *GuideViews*, while *TAviews*, although less significant, but still negatively associated with returns. As for the *AcademyViews*, we confirm our previous findings that attention to educational information is positively associated with portfolio performance even after controlling for investor past performance. Not surprisingly, we also observe strong persistence in investment performance and risk-taking as the coefficient estimates for the lagged performance variables are positive and highly statistically significant. We also perform these estimations on sample categories based on portfolio turnover, account tenure, and *AcademyViews* intensity similar to the analyses in Tables 5–7. Overall, these results confirm our findings reported in Tables 5–7.[14]

An alternative way to ensure that the observed relationship between attention and investment performance is not biased by the past performance is to look at the relationship between our attention measures for 2017 and the future performance measures for 2018. Once again, we do not have access to the attention measures for 2018 and hence are not able to carry out panel data analysis, but we are still able to observe the investment performance of almost 300 000 individual investors in 2018, given their attention allocation in 2017. We report these estimations in Columns 4–6 of Table 8 (and repeat the estimation for each category in Tables A5–A7 in the Online Appendix). The results of this analysis are comparable to our main results reported in Tables 4–7. As the signs and significance remain largely the same with only a few exceptions in the limited sub-sample analyses.

4.5. Other robustness tests

While we try to ensure the robustness of our results in different sub-sample estimations, certain limitations of our dataset may still potentially cause bias in our estimation results. The first concern regarding our analysis could be related to the argument that the documented relationship between attention to financial education and portfolio performance may be driven by the brokerage's new customers. This concern is partly reasonable as in addition to the differences in account tenure between the users and non-users of Academy pages observed in Table 2, one could argue that existing customers may have already accessed the Academy pages previously and are less likely to read them again, unlike those customers who have just opened their accounts. Although we partially address this issue by controlling for account tenure in all of our specifications, we still re-estimate our baseline regression models in two sub-samples of investors: those with *(i)* more than two years of account tenure, and *(ii)* less than two years of account tenure. This sampling allows us to separate new customers from

Table 8. Attention and investor performance: the role of past performance and previous attention

	Sharpe ratio	Return	StDev	Sharpe ratio 2018	Return 2018	StDev 2018
Gender	−0.182***	−0.018***	0.029***	−0.032***	−0.017***	0.058***
	(−36.42)	(−15.89)	(22.69)	(−11.65)	(−19.23)	(56.00)
Age	0.012**	−0.003**	−0.003***	0.017***	0.004***	−0.015***
	(2.39)	(−2.43)	(−3.42)	(5.49)	(3.56)	(−13.35)
AccountTenure	0.057***	0.015***	−0.014***	0.043***	0.014***	−0.030***
	(15.47)	(15.02)	(−16.47)	(26.49)	(24.42)	(−43.99)
Turnover	−0.051***	−0.007***	0.007***	−0.018***	−0.008***	0.006***
	(−53.76)	(−27.02)	(21.47)	(−32.64)	(−32.86)	(17.08)
Logins	0.049***	0.008***	−0.007***	0.007***	0.002***	−0.006***
	(30.43)	(19.01)	(−17.08)	(6.28)	(6.39)	(−14.32)
AcademyViews	0.166***	0.027***	−0.019***	0.020***	0.008***	−0.029***
	(44.37)	(25.79)	(−18.93)	(12.38)	(14.87)	(−41.33)
GuideViews	−0.066***	−0.008***	0.008***	−0.009***	−0.004***	0.013***
	(−58.05)	(−23.23)	(20.69)	(−17.19)	(−20.59)	(48.24)
TAviews	−0.005	−0.002*	−0.000	−0.003*	−0.001**	−0.001
	(−1.41)	(−1.87)	(−0.57)	(−1.87)	(−2.39)	(−1.36)
Sharpe2016	0.003***					
	(4.76)					
Return2016		0.054***				
		(11.01)				
StDev2016			0.402***			
			(19.60)			
Intercept	0.542***	−0.032***	0.175***	−0.278***	−0.097***	0.441***
	(18.09)	(−4.02)	(18.16)	(−20.07)	(−19.54)	(73.99)
Adj. R^2	5.5%	1.9%	28.0%	1.1%	1.6%	3.7%
N. Obs.	195,761	195,761	195,761	272,865	272,865	272,865

Note: This table presents the estimates of the ordinary least squares (OLS) analysis of the determinants of the Sharpe ratio, annualized standard deviation of returns, and the annual return of an investor. The baseline regression model is:

$$PerformanceMeasure_i = \alpha_i + \beta_i \times Demographic_i + \gamma_i \times Activity_i + \lambda_i \times Attention_i + \varepsilon_i,$$

where the dependent variable *PerformanceMeasure* is either the Sharpe ratio, annualized standard deviation of returns or annual return for an investor *i*. *Demographic* includes the natural logarithm of investor age and a dummy variable for the investor's gender (male = 1). *Activity* includes the natural logarithms of portfolio turnover and account tenure for an investor *i*. *Attention* is the attention behavior variables for *Logins, AcademyViews, GuideViews* and *TAviews. Logins* is the natural logarithm of the number of days the investor was logged into the investment account in 2017. *AcademyViews* is the natural logarithm of the number of Avanza Academy page views. *GuideViews* is the natural logarithm of the number of Avanza Guide page views. *TAviews* is the natural logarithm of the number of technical analysis views on the Avanza Guide pages. Columns 1–3 also include lagged by one year performance measures. In Columns 4–6 the performance measures, demographic, and activity variables are from 2018, while the Attention measures are lagged by one year (from 2017). The standard errors are White heteroscedasticity consistent. *,** and *** refer to statistical significance at the 10%, 5% and 1% levels, respectively. The t-statistics are in parentheses.

existing ones and cleans the effects of attention for customers with different client times. Given that our results remain unchanged in this sub-sample analysis (see Table A8 in the Online Appendix), we argue that attention to educational information is beneficial for both newly registered and existing trades as it is positively related to portfolio performance irrespective of investor experience measured by account tenure.

Another concern is that some of our measures of attention, as we explain in section 2.2, have a hierarchical order. First, an investor must log into the account before being able to view the Academy or Guide pages. Hence, the effect that we observe from the *AcademyViews* and *GuideViews* may potentially be driven by the overall investor attention to the portfolio. Second, an investor must view a Guide page before it is possible to view technical analysis since the technical analysis tools are available through the Guide pages. Therefore, the negative impact of *TAviews* on investor performance may be masked by *GuideViews*. We address this collinearity issue by orthogonalizing the attention variables.[15] We obtain *Orthogonal Logins* by using residuals from the OLS regression of *Logins* on turnover ratio. These residuals can be interpreted as general investor attention to the portfolio, which is not driven by the actual trading. Next, we obtain *Orthogonal AcademyViews* and *Orthogonal GuideViews* from residuals of two separate regressions of either *AcademyViews* or *GuideViews* on *Turnover* and *Orthogonal Logins*. Finally, we regress *TAviews* against *Turnover*, *Orthogonal Logins*, and *Orthogonal GuideViews* and use the residuals from this regression as *Orthogonal TAviews.* We also orthogonalize *AccountTenure* by regressing it on *Age* as older investors are likely to have more tenured accounts.

After forming the orthogonalized variables, we re-estimate Equation (2) with the orthogonalized attention variables. These results are presented in Table A9 in the Online Appendix. The findings from this analysis are similar to our main results reported in Table 4. As an additional check for collinearity across our attention variables, we still re-estimate all regression models where we assess the effect of regular attention variables one by one in separate regression models. These results are also qualitatively similar to the results from our main analysis and, therefore, are not reported in this paper.

We further assess the joint effect of different attention variables by analyzing the interactions of *Logins* with other attention variables (*TAviews, GuideViews, and AcademyViews*). This analysis is presented in Table A10 in the Online Appendix. The results indicate that the negative effects of attention to analytical information and technical analysis on portfolio performance are alleviated with more frequent portfolio attention. In addition, the results also suggest that the effects of investor attention to educational information on portfolio performance become even more pronounced with more frequent portfolio attention. While this analysis does not alter our main findings, the question of how the combination of different types of information affects individual investor performance would be an interesting extension of our paper. We leave this question as an avenue for future research.

Nevertheless, we are able to examine whether the intensity of attention affects our findings. As an additional analysis, we check for the difference between the extensive and intensive margins of the effect of our attention variables. To measure extensive margin we replace the investor attention variables – *GuideViews*, *AcademyViews,* and *TAviews* – with dummy variables taking a value of 1 if an investor pays attention to the corresponding type of information. To measure intensive margin we first create three subsamples of investors who pay attention only to *GuideViews*, *AcademyViews,* and *TAviews* and then estimate the relation between investor attention to the selected information and individual investor performance in each of the groups. The results show that both the extensive margin of investor attention – the decision to pay attention, and the intensive margin – the intensity of attention, have qualitatively similar effects compared to the results of our main analysis. The only exception is the relation between *TAviews* and Sharpe ratio, which becomes insignificant even though the results for standard deviation and return remain unchanged. These estimates are reported in Table A11 in the Online Appendix.

As an additional sub-sample analysis, we identify two types of investors: those who pay attention to financial education and not to analytical information (*Academy Users*) and those who pay attention to analytical information only and not to financial education (*Guide pages Users*). Panel A in Table A12 in the Online Appendix presents a means comparison of these two types of investors. As can be seen from the table, there are almost three times more investors who prefer information from the Guide pages rather than the Academy pages. However, there is also a distinct difference in the portfolio characteristics between these two groups of investors. *Academy Users* demonstrate a Sharpe ratio that is two times higher than for *Guide pages Users* and they have consistently higher returns and lower standard deviations. There is also a statistically significant difference between the other portfolio characteristics such as portfolio turnover, account tenure, and login frequency. Moreover, as can be seen in the table, these two groups of investors are quite different in terms of gender and age. It is, therefore, reasonable to conclude that very distinct groups of investors rely on different sources of information.

While we control for these differences in our baseline regression models, we check the robustness of these estimates in an additional matched sample analysis. Specifically, we match *Academy Users* and *Guide page Users* based on observable characteristics using the propensity score matching (PSM) technique. To perform PSM, we first define *Academy Users* as a dummy variable that has a value of one for investors who access the Avanza Academy pages and do not view the Guide pages, and zero for those who access the Guide pages and do not view the Academy pages. Then, we estimate a logit regression to predict the *Academy Users* dummy with the other portfolio and investor characteristics. These estimations are reported in Column 1 in Panel B in Table A12. Next, we use the closest predicted value from the logit regression to construct a one-to-one nearest-neighbor matched sample. This approach allows us to create a sample of investors who access different sources of information (financial education or analytical information) but who have similar characteristics otherwise. Given the variety of our rich dataset, we are able to match almost 65,000 individual investors.

We apply three matching criteria ranging from a broad match based on Account Tenure and Portfolio Turnover to a more conservative match based on all of the portfolio characteristics including login frequency and demographic characteristics such as gender and age.[16] Regardless of the matching criteria, the results of this sub-sample analysis are consistent with our previous finding on the value-enhancing attribute of investor attention to financial education and provide further support for our third hypothesis that *individual investor performance improves with higher attention to financial education*.

Furthermore, we perform an additional risk adjustment beyond our estimations with the Sharpe ratios. In particular, we include return variance in regressions with annual returns as an additional control variable. As expected, we observe a significant relationship between risk and return, and much better explanatory power of these models, but our main conclusions essentially remain unchanged and therefore we do not tabulate these results.

Finally, we allow for a potential non-linear relationship between portfolio performance measures and the variables of our interests. In particular, we generate four categorical variables for measures that are subject to a potential non-linear effect (*Age, Turnover, AccountTenure, Logins, TAviews, GuideViews, and AcademyViews*). Category 0 includes investors, where the measure of interest is equal to zero; Category 1, where the variable of interest is below its 33rd percentile of distribution; Category 2 for variables between 33% and 66%; and Category 3 for variables over 66%. For obvious reasons, *Age* and *AccountTenure* do not contain Category 0. Our main findings are again unaffected in the sub-category analysis and hence are not tabulated.

5. Conclusion

In this study, we examine how investor attention to portfolio information, analytical information, technical analysis and financial education affects portfolio performance. We confirm the results of Gargano and Rossi (2018) that portfolio attention is associated with better investment performance. However, when we consider investor attention to analytical information on specific stocks, we find that investor performance decreases with this attention.

As a novel feature to the previous literature, our data enable us to measure investors' page views of educational information, which measures investor attention to financial education. We find that investors who pay more attention to financial education demonstrate better investment performance. Overall, our evidence is broadly consistent with previous extensive evidence (e.g. Abreu and Mendes 2010; Von Gaudecker 2015; Bianchi 2018; Vaarmets, Liivamägi, and Talsepp 2019) showing that financial literacy is important for more favorable investment outcomes.

In addition, we are able to distinguish investor attention to technical analysis from investor attention to analytical information. In relation to the evidence of Hoffmann and Shefrin (2014) on the relative underperformance of investors who use technical analysis, we find that technical analysis is detrimental to performance only in the case of active traders. Other investors, who trade less frequently may, in turn, successfully manage portfolio risk and perform better if they use technical analysis.

Moreover, our findings suggest that investors who pay more attention to financial education do not experience a decline in performance from using technical analysis. In fact, the question of whether using technical analysis affects investment performance may depend on who is using those analytics.

The main lesson from our study is that investors appear to benefit more from considering their financial education and following their own portfolios instead of paying too much attention to analytical information. For practitioners, our study encourages brokerages and financial market intermediaries to make the material on financial education more available and to encourage investors to use it. The novel findings in this study indicate that more evidence on attention allocation within different types of investment vehicles and accounts is needed in order to provide more conclusive evidence on how investor attention affects portfolio performance. We leave this analysis for future research.

Notes

1. Avanza Bank was founded in 1999 and currently is one of the largest banks for retail trading based on the number of customers and capital market transactions in Sweden. Hence, the dataset under study can be considered as representative sample of Swedish retail traders. The data from the same source are also used in e.g. Davydov et al. (2017).
2. We are not able to obtain information on portfolio values as in Davydov et al. (2017) due to the new European General Data Protection Regulation (GDPR); portfolio values can potentially identify individual investors, as data on investment income are public information in Sweden.
3. If we were to use a negative interest rate as the risk-free rate in this situation, investors not investing in risky assets would show the difference between a zero and a negative interest rate as the excess return. However, we also carried out an analysis using the Stibor 3-month rate as the risk-free interest rate for robustness and the results remained qualitatively the same.
4. Extreme Sharpe ratios are those above the 99.5th percentile or below the 0.5th percentile of all the Sharpe ratios in the sample.
5. In a few cases when investors have multiple accounts, we use the aggregate value of these accounts to get the data per investor.
6. Formally, measures of investor attention are calculated as *Ln (1+number of days or number of views)*.
7. There are very few accounts with extreme portfolio turnover ratios that remained after winsorization. Such high values can be explained by the use of automated trading by a small number of investors. Nevertheless, we ascertain that these extremes do not drive our results in multiple tests discussed in Section 4 of this paper.
8. The minimum age of 1 could be explained by the possibility of opening and managing an account for an under-aged person. When the holder of an account is deceased, the account can still be managed as an estate. This option could explain the reported maximum age of 107. About 4% of our sample comprises accounts for customers younger than 18 and older than 82 years. This feature does not affect our findings, as we perform the analysis on an age-restricted sample in unreported robustness tests.
9. Given that all of our data come from one source, includes all observations (without repetitions) and do not contain a time-series dimension, clustering standard errors by cross-section are not justified. Nevertheless, for the sake of robustness we assign each investor to groups with respect to their attention or trading patterns and estimate clustered standard errors by groups. We do not report these estimates as they virtually remained unchanged and did not result in great variation in the reported standard errors.
10. The differences in portfolio turnover between users and non-users are statistically insignificant despite considerable differences in their mean values. We find this feature to be related to a very large variation in portfolio turnover across individual investors.
11. The estimation results without *Turnover* are qualitatively similar to the results reported in Table 3 with the only exception that *Age* becomes insignificant in explaining *GuideViews*. We do not tabulate these estimates for the sake of brevity.
12. We also check whether our results are driven by particularly active traders by re-estimating Equation (2) with more conservative winsorization of the turnover ratios, at the top 5%. The results are qualitatively similar to the results in Table 4 and hence are not reported.
13. Matching investors for two years resulted in the loss of a fraction of the observations due to missing data points. However, even in a reduced sample we obtain almost 200 000 individual investors, which is more than enough for powerful statistical tests.
14. We report these estimates in Tables A2-A4 in the Online Appendix.
15. Chang, Christoffersen, and Jacobs (2013) use similar approach in dealing with collinearity between skewness and kurtosis innovations.
16. We only report estimations for the Sharpe ratio. Estimations for return and standard deviation provide the same results and are therefore omitted for the sake of brevity, although they are available on request.

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