Appetite for Information and Trading Behavior

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Abstract

MiFID questionnaires came into force in November 2007, and provide the ideal opportunity for a natural field experiment to analyze how the attitude of retail investors towards financial information affects their trading activity. This study uses a random matching procedure that controls for socio-demographics, financial experience, education and various MiFID answers to analyze the trading characteristics of investors who only differ from others in their "appetite for information". We explore the hypothesis that the investors who voluntarily ask for financial information are de facto revealing a particular characteristic that may be indicative of their trading behavior. The results show that the investors who display an appetite for information tend to make smarter investments than their counterparts. Information-hungry investors execute fewer day trades, are less prone to the disposition effect, hold better quality and more diversified portfolios, and are more active on "complex" instruments. Ultimately, they earn higher (risk-adjusted) returns.

Keywords: retail investors, information acquisition, financial knowledge, MiFID

JEL Classification: D14, D83, G11, G28, G40

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1. Introduction

The Markets in Financial Instruments Directive (MiFID) came into force in November 2007.[1] Its goal is to increase the level of protection for retail investors by requiring investment firms to deliver the most suitable services to their clients. In this perspective, investment firms operating in the European Union are now obliged to collect information about their retail clients through the use of so-called "MiFID tests". Although the directive requires investment firms to gather relevant information about their clients' profiles, the quantity and the nature of the information to be collected depends on the types of service requested by the retail investor. As illustrated in Figure 1, MiFID determines three types of services: execution of orders, financial advice and portfolio management.

Investors who ask the banks to execute transactions on "complex" instruments have to complete the *Appropriateness test* (hereafter referred to as the A-test), which ensures that the client has the necessary experience and knowledge to understand the risks involved in "complex" financial instruments before investing. Investors who require financial advice or portfolio management also have to complete the *Suitability test* (hereafter referred to as the S-test). This assessment of suitability involves ensuring that the instruments and services offered meet the investor's objectives and financial capacity and are suited to his knowledge and experience in financial instruments. MiFID requirements are a perfect means to investigate the relationships between an individual need for information, i.e. asking for advice, and the trading behavior of retail investors.

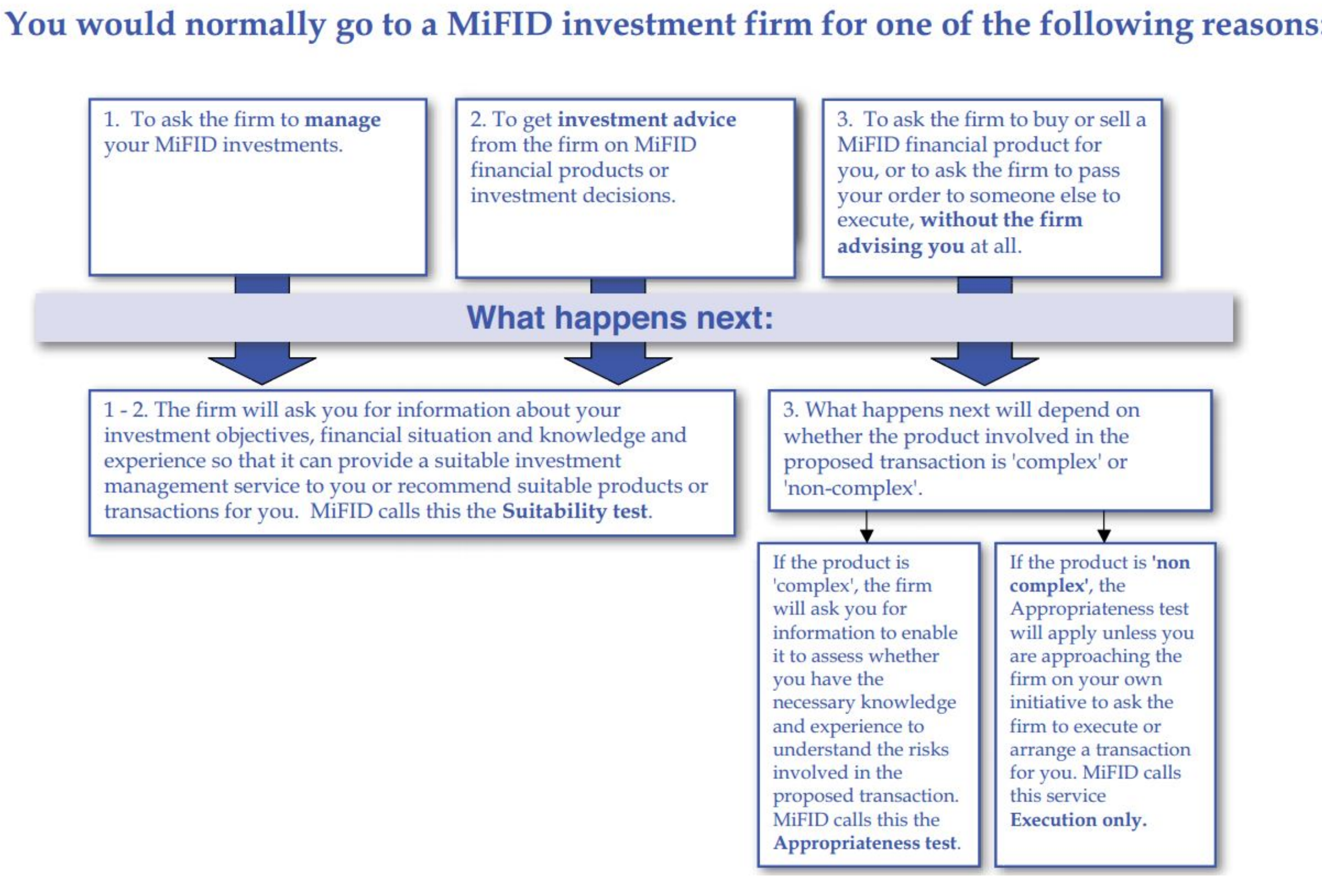
Our paper explores this topic through the use of a database obtained from an online Belgian brokerage house. The data details the MiFID questionnaire records of 14,155 retail investors and their trading activity over the 2008-2012 period. The online brokerage house did not offer any portfolio management service during the sample period, meaning that the investors in the sample have either completed the A-test to execute transactions (hereafter referred to as A-investors) or have completed the A-test and the S-test to access financial advice (hereafter referred to as S-investors). The online brokerage house under study provided S-investors with access to an information tool

[1] MiFID is applied in member states of the European Economic area (28 European member states and Iceland, Norway and Liechtenstein). Since January 2018, MiFID I (2004/39/EC) has been replaced by MiFID II (2014/65/UE) which has similar objectives.

on stocks as financial advice. By investing their time to complete the S-test,[2] S-investors show a desire to access a better service (i.e. a “premium service”) than a simple order execution request. We hypothesize that these investors have revealed a distinctive feature of their personality, that we refer to hereafter as “appetite for information”, which may be indicative of a specific trading behavior. In comparison, the A-investors have chosen to ignore a free access to professional recommendations. The aim of our paper is therefore to investigate whether there is a link between the appetite for information revealed (or not) by a retail investor when completing the MiFID questionnaires and his trading behavior. The utility of information provided by completed MiFID questionnaires has already been described in risk profile analysis (Mazzoli and Marinelli (2014)), sentiment trading (D’Hondt and Roger (2017)), mental accounting (Broihanne and Orküt (2018)) and subjective financial literacy (Bellofatto et al. (2018)). However, the present paper is the first to investigate whether the behavior of investors is consistent with the attitude they showed towards financial information when completing the MiFID questionnaires.

[2]It took an average of 30 minutes to complete the S-test.

Figure 1: MiFID services



The figure exhibits the three types of service recognized by MiFID and information investors need to provide accordingly. Source: Committee of European Securities Regulators (2008)

This paper makes a valuable contribution to financial information literature, which is characterized by a huge debate concerning the relationship between financial knowledge needs and financial knowledge acquisition. Although some authors argue that only financial education is needed to make investments, others suggest that financial advice could be a good solution for the lack of financial knowledge among individual investors (a.o. Bucher-Koenen and Koenen (2010) and Georgarakos and Inderst (2014)). Financial advice and financial knowledge would therefore be substitutes for each other. In the opposite vein, another approach considers financial advice and financial knowledge as complementary (Calcagno and Monticone (2015)). However, our paper differs from these papers insofar that it does not investigate the benefits of financial information (received from a financial advisor) *per se* but rather seeks to identify the personal characteristics that lead individual investors to voluntarily ask (or not) for useful financial information and evaluate how they affect their trading behavior.

Our results indicate that the decision to seek or forgo information is indicative of trading behavior. We find that the investors who reveal an appetite for financial information (S-investors) make smarter investments. They execute fewer day trades, are less prone to the disposition effect, hold better quality and more diversified portfolios and are more active on “complex” instruments, indicating a higher level of financial experience and familiarity with financial markets. In contrast, the A-investors display more “intuitive” trading behavior. They concentrate their trades on a lower number of stocks, execute more day trades and roundtrips on this stock set and are less attracted by “other-than-stocks” instruments. This “intuitive” trading behavior confirms the findings of D’Hondt and Roger (2017), who show that A-investors are more prone to trading on sentiment than S-investors and reveal that their trading behavior is more predictive of future returns on a long/short portfolio based on size than that of S-investors. Evidence of this difference in trading behavior may explain why S-investors earn significantly higher (risk-adjusted) returns. These findings hold even under a random matching procedure that controls for socio-demographic data, financial experience, education and various MiFID questionnaire answers.

These results contribute to the literature on the relationships between information acquisition and trading activity. Although several papers (a.o., Abreu and Mendes (2012) and Tauni et al. (2015)) report empirical[3] evidence of the positive relationship between information acquisition and trading activity, this is solely descriptive and is based on written answers to surveys, without considering trading records.[4] Furthermore, these authors focus purely on trading frequency and do not analyze trading behavior in a broader sense or even trading performance. To the best of our knowledge, the paper by Guiso and Jappelli (2006) is the only exception: in contrast to Abreu and Mendes (2012) and Tauni et al. (2015), they use a detailed database including the trading records

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[3]This topic of research has already been addressed from a theoretical point of view. In theoretical models, information investment is rational for investors as long as the cost of seeking information exceeds its marginal benefit. Certain authors (a.o. Grossman and Stiglitz (1980), Karpoff (1986) and Holthausen and Verrecchia (1990)) claim that the investors who spend more time searching for information tend to compensate the cost of information by taking more risky positions and by trading more. However, Argentesi et al. (2010) have a slightly different perspective. They argue that: “*The fact that more information is collected by investors does not necessarily imply that more trading will follow (for instance, because information may just suggest that it is optimal not to trade)*”.

[4]Abreu and Mendes (2012) use a survey conducted in 2000 by the Portuguese Securities Market Commission in which 1,559 investors were interviewed. Tauni et al. (2015) analyze the survey results of 333 individual investors in Chinese future markets. Both papers surveys ask questions such as “How often do you buy and sell financial assets?”.

and survey answers of 1,834 clients of a leading Italian commercial bank to investigate what determines the acquisition of information and how the latter affects trading behavior and performance. They provide evidence of a negative relationship between information acquisition and returns, supporting the overconfidence hypothesis. These authors find that the investors who spend more time searching for financial information are associated to frequent trading, less diversified portfolios and a lower tendency to delegate.

Our study differs from that of Guiso and Jappelli (2006) not only in terms of the sample size, which is larger and more recent in the present study, but also in the proxies used to measure investors' attitude towards information acquisition. While Guiso and Jappelli (2006) use a questionnaire to measure the time spent acquiring financial news from different sources of information (such as newspapers internet, etc.), the S-investors in our sample voluntarily complete the S-test to access a directly usable information tool. Since these investors have made an "effort" to access an information tool, our measure may be more indicative of their appetite for information.

The remainder of this paper is structured as follows. Section 2 describes the data. Section 3 describes the methodology we use. We report our empirical work and its results in Section 4. Section 5 concludes.

2. Data and Sample

The database is provided by an online Belgian brokerage house and encompasses the trading activity of 14,155 retail investors over the January 2008-March 2012 period.[5] It is composed of two datasets. The first contains information about the investors and is classified into three categories. The first category includes socio-demographic data: year of birth, gender and spoken language. The second category contains the answers to the A-test while the third category is composed of the answers to the S-test. The second dataset contains detailed information about the investors' trading activity on stocks, funds, options, warrants, and bonds.

This study uses stock trading activity information to build end-of-month portfolios for each in-

[5] D'Hondt and Roger (2017) and Bellofatto et al. (2018) analyze the same database but focus on different samples, according to their research questions.

vestor in the sample.[6] The resulting dataset is completed with Eurofidai[7] and Bloomberg[8] historical data to compute the market value of the end-of-month portfolios.

2.1. Trading activity

Our sample of investors made 654,678 trades on 5,959 different stocks,[9] which corresponds to 154,000 trades in a typical year and about 13,000 trades in a typical month. The investors in our sample are net buyers, since 60% of the trades are purchases and 40% are sales. Table 1 presents descriptive statistics for trading activity. The average investor completes 44 trades on 12 different stocks over a 25-month trading period.[10] For a given stock, a typical investor will trade the same stock an average 3.37 times over his whole trading period, of which 1.4 are day trades.[11] Concerning trading activity on "complex" instruments, the average investor completes around 7 trades in investment fund shares, 8 trades in options or warrants and almost no trade in bonds. All the above variables are positively skewed since the means are substantially larger than the medians.

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[6]In our sample, we only consider investors who began to trade at the brokerage house under study after January the 1st, 2008, i.e. after the MiFID tests came into force. We therefore assume that these investors have completed the tests before trading.

[7]www.Eurofidai.org

[8]www.Bloomberg.com

[9]We focus on stocks for which an ISIN code is available. For stocks traded in foreign currencies, we use exchange rates to convert monetary volumes into euros.

[10]We compute the trading experience as the difference between the last trade date and the first trade date available in the sample. As set out in Glaser and Weber (2009), we exclude any investors with less than 5 months of trading activity.

[11]We compute 1 day trade each time an investor makes a purchase and a sale in the same stock on the same day.

Table 1: Descriptive statistics for trading activity

	Mean	Median	Q1	Q3
Number of stock trades	44	18	8	45
Number of different stocks traded	12	7	4	15
Trading experience (in months)	25	24	14	35
Number of daytrades	1.43	0	0	0
Average number of trades on the same stock	3.37	2.4	1.75	3.64
Number of fund trades	7.04	0	0	0
Number of option trades	8.31	0	0	0
Number of bond trades	0.08	0	0	0

The table reports the cross-sectional mean, median, lower and upper quartiles for trading activity variables on a per investor basis over the sample period. 'Number of stock trades' is the number of trades executed on stocks. 'Number of different stocks traded' is the number of different stocks traded during the whole trading period. 'Trading experience' is computed as the difference between the last trade date and the first trade date available in the sample. It is expressed in number of months. 'Number of daytrades' is the number of times an investor makes a purchase and a sale on the same stock on the same day. 'Average number of trades on the same stock' is the average number of trades an investor makes on the same stock. 'Number of fund trades' is the number of trades executed on investment fund shares. 'Number of option trades' is the number of trades executed on both options and warrants. 'Number of bond trades' is the number of trades executed on bonds.

Table 2 shows statistics computed on binary variables. While 21.79% of the investors trade investment fund shares, 18.26% of them trade options or warrants, but only 3.16% of them trade bonds.

Table 2: Frequencies of trading activity on "complex" instruments

	0	1
Funds_trader	78.21%	21.79%
Options_trader	81.74%	18.26%
Bonds_trader	96.84%	3.16%

The table reports the frequencies of trading activity on "complex" instruments over the sample period. 'Funds_trader' is set to 1 when the investor made at least one trade on investment fund shares. 'Options_trader' is set to 1 when the investor made at least one trade on either options or warrants. 'Bonds_trader' is set to 1 when the investor made at least one trade on bonds.

As mentioned earlier, we use data on the trading activity in stocks to build end-of-month portfolios. Combining our data with historical market data, we compute the monthly average number of stocks held in the portfolios, the monthly average portfolio value and the monthly returns.[12]

Table 3 reports descriptive statistics for the above measures. We know that the average investor holds a four-stock portfolio, and this under-diversification is in line with the findings of Kumar and Lee (2006) and Polkovnichenko (2010) for the US and Broihanne et al. (2016) in Europe (France). The median of 2.76 is also consistent with the results of Goetzmann and Kumar (2008), who find that more than 50% of the retail investors in their sample hold one to three stocks. The average end-of-month portfolio value is about 22,000 euros, with a median of 6,500 euros. All these portfolio-based variables are positively skewed.

The average investor earns a monthly gross (net[13]) return of 0.40 (-0.40)% in a typical month.[14] The average monthly volatility of the returns is about 18%, with a median of 11.22%. The higher mean and median volatility than those reported in Dorn and Huberman (2005) could be explained by the specificity of our sample period.[15] In addition, the mean value of 18% is slightly higher than the monthly realized volatility of the BEL20 and CAC40 indices, which may represent appropriate benchmarks for Belgian investors over the 2008-2012 period.

The descriptive statistics depict a huge heterogeneity in the behavior and performance of the investors in our sample, and this is particularly in line with the extant literature on retail investors (Barber and Odean (2013)).

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[12]To compute trading performance, we make one assumption commonly used in the literature (Barber and Odean (2000), Barber and Odean (2001a), Shu et al. (2004) and Glaser and Weber (2007)), namely that all transactions take place on the last day of the month. Barber and Odean (2000) have shown that this simplifying assumption do not bias the measurement of portfolio performance.

[13]Only explicit transactions costs are considered.

[14]For each investor, we compute a geometric average return.

[15]They investigate the 1995-2000 period, while we analyze the post-2008 period.

Table 3: Descriptive statistics for end-of-month portfolio data

	Mean	Median	Q1	Q3
Number of stocks	4.25	2.76	1.36	5.29
Portfolio value (€)	22,005	6,490	2,195	17,779
Gross return (%)	0.40	0.23	-1.47	1.98
Net return (%)	-0.40	-0.22	-2.21	1.48
Volatility (%)	18.01	11.22	7.17	18.29

The table reports the cross-sectional mean, median, lower and upper quartiles for portfolio data variables on a per investor basis over the sample period. 'Number of stocks' is the monthly average number of stocks held in portfolio. 'Portfolio value' is the monthly average end-of-month portfolio market value. 'Gross return' is the geometric average of the monthly gross returns. 'Net return' is the geometric average of the monthly net returns. 'Volatility' is the standard deviation of the monthly returns.

2.2. A- and S-investors

Our sample is composed of two categories of investors that we can distinguish through the services they have requested and the information they have provided. In the first category, a total of 6,913 investors asked the bank to simply execute their transactions. According to MiFID, these investors had only completed the Appropriateness test (A-investors). In the second group, 7,242 investors had also requested access to an information tool on stocks. These investors had therefore also fulfilled the Suitability test (S-investors). As a consequence, while both groups execute trades by themselves, the S-investors have free access to a stock investment advice tool. The only "cost" to access the information tool is spending time (about 30 minutes) completing the S-test. In our case, the S-test under scrutiny is composed of 11 questions that cover the investor's objectives, financial capacity and knowledge and experience of financial instruments, as required by the MiFID directive.

Since both groups have completed the A-test, the information contained in this test can be used to characterize the overall profile of our investors. The A-test in our database consists of a list of categorical questions for which the investors have to select an answer.[16] We also have information

[16] Some questions were grouped together when they were related to the same topic. For example, the A-test contains detailed questions regarding the investor's knowledge of options, future contracts, warrants, structured products, etc. Given the low frequencies, we decided to group these elements together and create a single question related to the knowledge of "complex" instruments.

about certain socio-demographic variables.

Table 4 reports how the investors are distributed across the different categories for each question. It reveals that 8.04% of the investors chose the highest level when they had to estimate their level of financial markets knowledge. For the second question, approximately 5% of the investors evaluated their experience in options, structured products, Forex and future contracts to be "good", while 9.98% considered them to be "average", and the remaining investors said that they had no experience. Furthermore, around 34% of the investors had already invested at least once in an option, a structured product, a Forex instrument or a future contract. As for the level of education, 72% indicated that they had a university degree or equivalent, 21% had a secondary/high school qualification and 6% no qualifications at all. A majority of investors were male and spoke Dutch as their main language. The average investor is 44 years old (information not reported in the table). Finally, about 17% of the investors in our sample claim to have executive responsibilities.

Table 4: Statistics for investors' characteristics

	Empirical frequencies (%)
Self-estimated knowledge of financial markets	
Level 0	29.21
Level 1	30.99
Level 2	31.76
Level 3	8.04
Self-evaluated experience in "complex" instruments	
Level 0	84.71
Level 1	9.98
Level 2	5.31
Investment in "complex" instruments	
No	66.13
Yes	33.87
Level of education	
Level 0	6.09
Level 1	21.49
Level 2	72.42
Gender	
Female	14.80
Male	85.20
Language	
French-speaker	45.35
Dutch-speaker	50.77
English-speaker	3.88
Professional status	
Executive	16.67
Other	83.33
N	14,155

The table reports empirical frequencies for investors' characteristics. For the self-estimated knowledge of financial markets, level 0 is associated with a basic knowledge while level 3 refers to an experienced investor who manages all aspects of financial markets. For the self-evaluated experience in "complex" instruments, levels 0, 1 and 2 correspond respectively to 'no experience', 'average experience' and 'good experience' in options, structured products, Forex and future contracts. The response to investment in "complex" instruments is 'yes' if the investor states to have already invested in options, structured products, Forex or future contracts, and 'no' otherwise. Level of education is one of level 0 ('no qualification'), level 1 ('secondary school/sigh school qualification') and level 3 ('university degree'). Gender is 'female' if the investor is a woman and 'male' if the investor is a man. Language is 'French-speaker' if the investor speaks French as his main language, 'Dutch-speaker' if the investor speaks Dutch as his main language and 'English-speaker' if the investor speaks English as his main language. Professional status is 'executive' if the investor claims executive responsibilities and 'other' in all other cases.

3. Methodology

The A- and S-investors both execute trades unaided, but the S-investors have also voluntary requested access to additional information. Aside from having fulfilled the A-test, the S-investors have invested time in completing the S-test to access the advice tool. We therefore consider that they have revealed a particular appetite for information that may be related to their trading behavior. In contrast, the A-investors have forgone free access to more financial information. The aim of this paper is to compare the trading behavior of these two types of investor. However, since the investors who request financial information may differ from the others in a large set of covariates, comparing the trading behavior of the A- and S-investors to study the "appetite for information effect" may be subject to the "omitted variable" bias.[17] Any difference in the trading behavior between both groups of investors could consequently be due to other investor-immanent effects that are correlated with appetite for information.

Table 5 compares the A- and S-investors in terms of the variables displayed in Table 4. For each categorical variable, it reports the proportion of each type of investor, the difference between these proportions and the significance thereof. Table 5 clearly highlights that the A- and S-investors significantly differ for the vast majority of the variables. We therefore need to control the effect of these variables to investigate the impact of appetite for information. As stated in Stuart (2010), it is desirable when estimating causal effects using observational data to replicate experiments as closely as possible by obtaining treated and control groups with similar covariates distributions. In this perspective, we applied a random matching method that has frequently been used in the literature (such as Gerhardt and Hackethal (2009) and Kramer (2012)).

According to Stuart (2010), nearest-neighbor matching is one of the most common and easily implemented matching methods. In its simplest form, 1:1 nearest neighbor matching selects the closest control individual to each individual i. The distance between two individuals is based on their respective propensity score, defined by Rosenbaum and Rubin (1983) as the probability of receiving the treatment given the observed covariates. The propensity score is advantageous because it facilitates the construction of matched sets with similar distributions of covariates, without

[17] On the paper of Bluethgen et al. (2008) that compares the trading behavior of advised and non-advised investors, Gerhardt and Hackethal (2009) claim that many aspects of the difference between advised and non-advised investors can be attributed to differences in investors' characteristics.

Table 5: Comparison of the A- and S-investors' characteristics

	A-investors (%)	S-investors (%)	Difference (%)
Self-estimated knowledge of financial markets			
Level 0	29.30	29.12	-0.18
Level 1	31.01	30.97	-0.04
Level 2	30.72	32.74	2.02***
Level 3	8.97	7.17	-1.80***
Self-evaluated experience in "complex" instruments			
Level 0	82.77	86.57	3.8***
Level 1	11.10	8.91	-2.19***
Level 2	6.13	4.52	-1.61***
Investment in "complex" instruments			
No	67.08	65.23	-1.85**
Yes	32.92	34.77	1.85**
Level of education			
Level 0	7.03	5.19	-1.84***
Level 1	22.90	20.15	-2.75***
Level 2	70.07	74.66	4.59***
Gender			
Female	18.91	10.88	-8.03***
Male	81.09	89.12	8.03***
Language			
French-speaker	47.62	43.19	-4.43***
Dutch-speaker	48.36	53.08	4.72***
English-speaker	4.02	3.73	-0.29
Professional status			
Executive	15.15	18.12	2.97***
Other	84.85	81.88	-2.97***
N	6,913	7,242	

The table reports the empirical frequencies of the A- and S-investors for each categorical variable displayed in Table 4. The last column reports the difference between the A- and S-investors and its significance. *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.

requiring close or exact matches on any of the individual variables (Stuart (2010)).

The propensity score is computed for each investor in our sample by building a logit model where the dependent variable is a binary variable of 1 if the investor has asked for an access to the information tool, and 0 otherwise. For the independent variables, Stuart (2010) suggests that matching using propensity scores must include variables associated with both the treatment (i.e. filling in the S-test) and the outcome (i.e. trading behavior). Our choice of independent variables is therefore dependent upon the results published in the literature for each of the two following goals.

First, we aim to include variables that are known to be associated with the demand for financial advice, i.e. financial literacy (Hackethal et al. (2012), Collins (2012), Georgarakos and Inderst (2014) and Calcagno and Monticone (2015)), education (Chalmers and Reuter (2010)) and socio-demographics (Bluethgen et al. (2008), Haslem (2008) and Gerhardt and Hackethal (2009)). In this respect, the level of financial literacy is evaluated via the first variables of Table 4 for self-assessed knowledge and experience. The level of education and socio-demographic variables (gender, professional occupation, age) are also found in the answers to the A-test.[18]

Second, we must also add variables that are associated with trading behavior. Again, the literature describes how socio-demographic variables impact trading decisions and financial activity: women hold less risky assets than men (Bernasek and Shwiff (2001), Dwyer et al. (2002), Agnew et al. (2003), Charness and Gneezy (2012)), and age has an impact on the mix of risky assets, although it is not clear if the young invest more (Ackert et al. (2002)) or less in stocks (Shum and Faig (2006)) than older counterparts. Grinblatt and Keloharju (2001) show that native tongue and culture also have an impact on stockholdings and trades. In our data, as the language variable indicates the main language of the investor (investors are often multilingual), we include it in the matching score determination. Financially literate households are known to invest more in stocks (Van Rooij et al. (2011), Balloch et al. (2014)) and in derivatives (Hsiao and Tsai (2018)). In fact, the variables that impact the demand for advice are also associated with trading behavior. Guiso and Jappelli (2006) have already revealed that high trading frequency is observed for investors looking for information. This is confirmed by Hackethal et al. (2010), who show that investors

[18]For categorical variables, we only include N-1 dummy variables in the logit model. We consider the lowest level as the category of reference.

who rely on advisors have high trading volumes. As trading frequency and trading volumes are not always directly observed, trading activity is often proxied by portfolio size. Glaser (2003), Vissing-Jorgensen (2003) and Abreu and Mendes (2012) have shown that portfolio size does indeed have an impact on trading activity. Broihanne et al. (2016) also demonstrate that portfolio value is an important determinant of diversification choices. Dorn and Huberman (2005), Guiso and Jappelli (2008), Goetzmann and Kumar (2008) find that investors with high portfolio size hold better quality and more diversified portfolios and earn higher returns. Finally, Nicolosi et al. (2009) show that the trading performance of individuals appears to improve with trading experience. For these reasons, our logit model also controls for portfolio value and trading experience.

Other papers on financial information and trading behavior build on the matching procedure to create homogenous samples. Gerhardt and Hackethal (2009) use gender, age, marital status, risk tolerance, customer experience and deposit value to build comparative subsamples. Kramer (2012) matches across variables of gender, age, residential value, income, portfolio and equity allocation. In contrast to our study, the aforementioned papers specifically investigate the effect of advice received from a financial advisor on trading behavior. To the best of our knowledge, the only paper that uses a similar database to ours to analyze the effect of financial information acquisition from other sources on the trading behavior of retail investors is that of Guiso and Jappelli (2006). However, while the latter identify socio-demogaphic variables (wealth, risk tolerance and the level of education) as determinants of the search for financial information, they do not apply random matching,[19] nor do they investigate the effect of financial literacy.

Based on the propensity score, we associate the "closest" A-investor ("twin" A-investor) for each S-investor within a specific caliper width. According to Austin (2011), the optimal caliper width is 0.2 of the standard deviation of the logit of the propensity score. Since we have more S-investors than A-investors, we perform random matching with replacement (i.e. one A-investor can be matched with several S-investors).

[19]They use an instrumental variable approach instead.

4. Results

4.1. Matching results

Table 6 reports the results of the logit model used to compute the propensity score. As for financial literacy, the investors who perceive themselves as highly literate and experienced in "complex" instruments are less likely to display an appetite for financial information. It is to some extent consistent with Hung and Yoong (2010), Georgarakos and Inderst (2014) and Calcagno and Monticone (2015), who all provide evidence that self-perceived financial literacy is negatively correlated to the demand for financial advice. By contrast, investors in our study who claimed to have invested in "complex" instruments are more likely to be information seekers. While this phenomenon may seem surprising, our result is consistent with those of Calcagno and Monticone (2015).[20]

Results for the level of education suggest that the most educated investors in our sample tend to display a higher appetite for information. These findings are consistent with those of Hung and Yoong (2010), Collins (2012), Hackethal et al. (2012), and Hoechle et al. (2017), who report that the likelihood of an investor asking for financial advice increases with the level of education. Our findings concerning the search for financial information are in line with those of Guiso and Jappelli (2006), who show that the most educated investors tend to spend more time looking for financial information than their counterparts. According to these authors, the level of education is a proxy for a lower cost of information.

For the professional status variable, the investors who claim to have executive responsibilities tend to display a higher appetite for financial information. This is in contrast with Bluethgen et al. (2008) and Hackethal et al. (2012), who do not observe any effect of executive responsibilities on the demand for financial advice. Furthermore, our data shows that being a male significantly increases the appetite for information, thus confirming the findings of Guiso and Jappelli (2006). However, unlike previous studies, age does not seem to have any significant effect. Finally, investors with more trading experience are more likely to complete the S-test and ask for more information. This is in line with Gerhardt and Hackethal (2009) to some extent, although the latter show that the investors' ex-ante trading experience is positively related to the decision to refer to a

[20]They provide evidence that while subjective financial literacy is negatively correlated to the demand for financial advice, objective financial literacy has the opposite effect.

financial advisor.

A sample of homogeneous investors was built, based on the propensity score. It contained 7,242 S-investors and 3,819 "matched" A-investors (i.e. an A-investor selected in the matching procedure has been matched with an average of two S-investors). According to Stuart (2010), the two most common numerical balance diagnostics to assess the quality of a matching are the standardized difference of the means of the propensity score and the ratio of the variances of the propensity score in the treated and control group. Rubin (2001) states that the standardized difference of means should be less than 0.25 and the variances ratio should be between 0.5 and 2. In our matched sample, the standardized difference of means of the propensity score is 0.13 while the variances ratio is 0.92, which indicates a correct matching procedure. Figure 2 provides other evidence of the quality of our matching procedure. Distributions of the propensity score for the A-investors ("0") and S-investors ("1") before/after matching are reported. It shows that the propensity score distribution of the A-investors is closer to that of S-investors after matching.

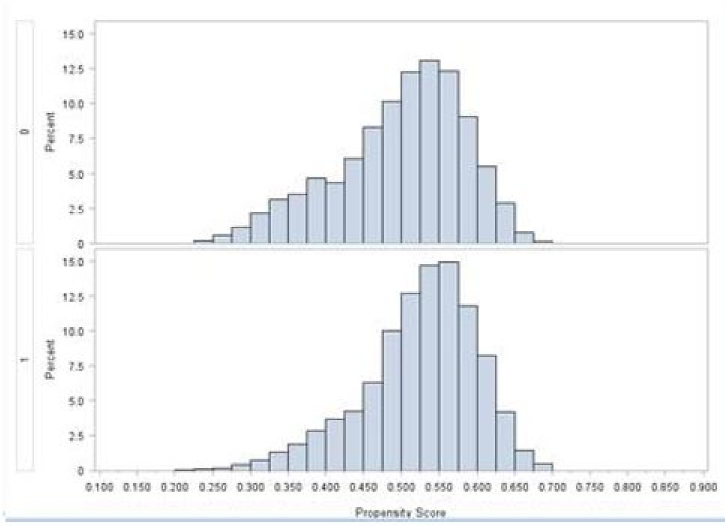
Table 6: Determinants of appetite for information

Independent variables	Parameter estimates
Intercept	-1.0138***
Self-estimated knowledge of financial markets 1	-0.0671
Self-estimated knowledge of financial markets 2	-0.0532
Self-estimated knowledge of financial markets 3	-0.2697***
Self-evaluated experience in “complex” instruments 1	-0.2902***
Self-evaluated experience in “complex” instruments 2	-0.3251***
Investment in “complex” instruments “Yes”	0.1484***
Level of education 1	0.2121***
Level of education 2	0.3757***
Male	0.6137***
French-speaker	-0.1860***
English-speaker	-0.1798**
Executive	0.1366***
Age	-0.00106
Ln(PF value)	0.0174
Trading experience	0.00965***
Pseudo R^2	1.94%
N	14,155

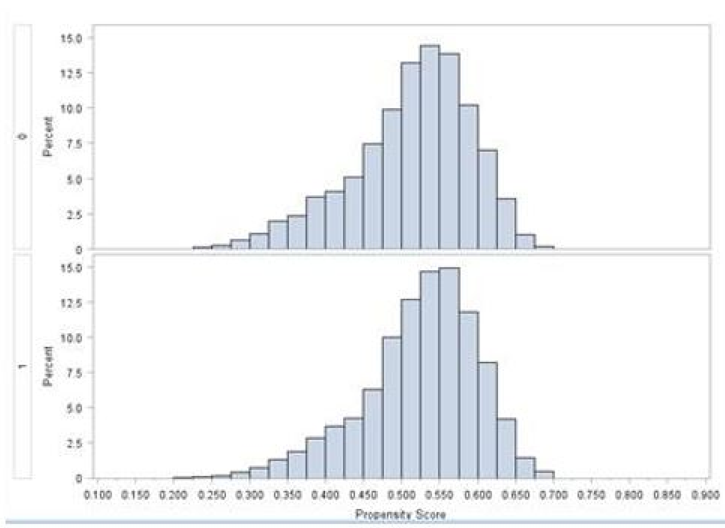
The table reports parameter estimates of a logit model in which the dependent variable is a binary variable with a value of 1 if the investor has asked for an access to the information tool on stocks and has completed the S-test and 0 otherwise. The set of independent variables includes the variables presented in Table 4. It includes three dummy variables for the three highest levels of self-estimated knowledge of financial markets, two dummy variables for the two highest levels of self-evaluated experience in “complex” instruments, a dummy variable with a value of 1 if the investor claims to have already invested in “complex” instruments, a dummy variable with a value of 1 if the investor states to have a secondary/high school degree, a dummy variable with a value of 1 if the investor states to have a university degree, a dummy variable with a value of 1 if the investor is a male, a dummy variable with a value of 1 if the investor speaks French as his main language, a dummy variable with a value of 1 if the investor speaks English as his main language and a dummy variable with a value of 1 if the investor claims executive responsibilities. The model also includes age, the natural logarithm of the monthly average end-of-month portfolio market value and trading experience. *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.

Figure 2: Propensity score distributions

Before Matching



After Matching



This figure exhibits the propensity score distributions for the A-investors (“0”) and S-investors (“1”) before and after matching.

4.2. Trading behavior comparison results

In this section, a univariate analysis is used to investigate whether the A- and S-investors display different trading behaviors. To this end, we distinguish between three categories of variables that characterize trading behavior: trading activity, diversification and performance.

Trading activity is measured using the number of stock trades, the number of day trades and the average number of trades on the same stock. We also consider whether investors trade options or warrants and bonds and take into account the retail investors’ exposure to the disposition effect (hereafter referred to as DE). This well-known behavioral bias reflects the investors' reluctance to suffer losses (i.e. they keep "losers") as well as their propensity to realize gains (i.e. they sell "winners"). We apply the methodology of Odean (1998) to assess the DE at an individual level by computing the difference between the proportion of gains and the proportion of losses.[21]

For the measures of diversification, we build on the procedure described by Bellofatto et al. (2018) and use the number of different stocks traded during the whole period, which approximates an investor's investment universe, the monthly average number of stocks held in portfolio and the volatility of monthly returns. We also consider whether investors trade investment funds. As suggested in Goetzmann and Kumar (2008) and Koestner et al. (2017), we add the monthly average Herfindahl-Hirschman Index (referred to hereafter as HHI). Computed as the sum of squared stock portfolio weights, HHI is a measure of portfolio concentration that ranges from 0 (for well-diversified portfolios) to 1 (for under-diversified portfolios containing just one stock). For investors who hold monthly positions in investment funds, we build on Dorn and Huberman (2005) and Koestner et al. (2017) by computing a modified Herfindahl-Hirschman Index (referred to hereafter as MHHI) in which any position in funds is replaced by a portfolio of 50 equally-weighted securities.

The geometric averages of both gross and net returns are used to measure performance. We also consider gross and net Sharpe ratios as risk-adjusted measures of performance.

Table 7 reports the comparison of the trading behavior between the "matched" A- and S-investors. It exhibits for each variable the mean of both groups of investors, the difference between groups and the significance thereof. As suggested by Stuart (2010), we consider the number of times an A-investor has been selected as a match by using a frequency weights in the mean comparisons. The results suggest that the A- and S-investors differ significantly in their trading behavior, even after controlling for a wide set of investors' characteristics. The differences in the volatility and the net Sharpe ratio are the only exceptions.

For trading activity, while the S-investors make more trades, the A-investors make more day trades and roundtrips on the same stock. Furthermore, the S-investors are more likely to invest in

[21] We compute on a daily basis the number of paper/realized gains and losses over the whole trading period for each investor and each position in his portfolio. We then sum all those paper/realized gains and losses to compute the proportion of gains and losses realized for each individual.

more “complex” instruments and display a lower exposure to the DE, which may suggest a higher level of financial experience and more familiarity with financial markets (Bellofatto et al. (2018)).

As far as diversification is concerned, the S-investors trade on a larger stock universe and tend to hold better diversified portfolios. Those investors include a higher number of stocks in their portfolios and are more likely to invest in investment funds. The HHI of the S-investors’ portfolios is significantly lower than that of the A-investors. This finding is even more convincing when the monthly holding in funds in the MHHI is taken into account. This finding differs from that of Guiso and Jappelli (2006) who report that the most information-seeker investors tend to have less diversified portfolios and tend to invest more in individual stocks. However, these authors use the proportion of the portfolio invested in funds as a proxy for diversification.

Finally, the S-investors display, on average, higher monthly gross and net returns than the A-investors. Here again, our results do not support those of Guiso and Jappelli (2008), who find a negative relationship between information acquisition and returns. On a risk-adjusted basis, this result only holds for the gross Sharpe ratio.

Table 7: Univariate comparison results for trading behavior between “matched” A- and S-investors

	“matched” A-investors	S-investors	Difference
Number of stock trades	43.658	48.457	4.799***
Number of daytrades	1.6331	1.3694	-0.2637*
Average number of trades on the same stock	3.7095	3.1540	-0.5555***
Proportion of option traders (%)	17.16	19.41	2.25***
Proportion of bond traders (%)	2.39	4.03	1.64***
DE (%)	17.7230	16.5495	-1.1735*
Number of different stocks traded	10.7211	13.6081	2.8870***
Number of stocks	3.7636	4.8258	1.0623***
Volatility (%)	18.5101	17.7121	0.7980
Proportion of fund traders (%)	16.09	27.51	11.42***
HHI (%)	58.05	51.00	-7.05***
MHHI (%)	58.05	45.99	-12.06***
Gross return (%)	0.172	0.506	0.334***
Net return (%)	-0.604	-0.338	0.266***
Gross Sharpe ratio	-0.00991	0.00684	0.0167***
Net Sharpe ratio	-0.0735	-0.0767	-0.00325
N	3,819	7,242	

The table reports for each variable the mean for “matched” A- and S-investors, the difference between groups of investors and the significance thereof. ‘Number of stock trades’ is the number of trades executed on stocks over the sample period. ‘Number of daytrades’ is the number of times an investor makes a purchase and a sale on the same stock on the same day over the sample period. ‘Average number of trades on the same stock’ is the average number of trades an investor makes on the same stock over the sample period. ‘Proportion of option traders’ is the proportion of investors who trade either options or warrants at least once over the sample period. ‘Proportion of bond traders’ is the proportion of investors who trade bonds at least once over the sample period. ‘DE’ refers to the disposition effect computed at the individual level as the difference between the proportion of gains realized and the proportion of losses realized. ‘Number of different stocks traded’ is the number of different stocks traded during the whole trading period. ‘Number of stocks’ is the monthly average number of stocks held in portfolio. ‘Volatility’ is the standard deviation of the monthly returns. ‘Proportion of fund traders’ is the proportion of investors who trade investment fund shares at least once over the sample period. ‘HHI’ is the monthly average Herfindahl-Hirschman Index, which is computed as the sum of squared stock portfolio weights. ‘MHHI’ is a modified version of the HHI for which any position in funds is replaced by a portfolio of 50 equally-weighted securities. ‘Gross return’ is the geometric average of the monthly gross returns. ‘Net return’ is the geometric average of the monthly net returns. ‘Gross Sharpe-ratio’ is a risk-adjusted measure of gross return. ‘Net Sharpe-ratio’ is a risk-adjusted measure of net return. *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.

5. Conclusion

In this paper, we use the unique opportunity offered by our data to test whether the investors who voluntarily ask for an information tool differ in their behavior from those who do not. Specifically, we investigate whether the investors displaying a distinct feature, which we call "appetite for information", trade differently than the investors who do not request access to additional financial information. We identified this distinct feature through the mandatory MiFID tests. After controlling for trading and personal characteristics, the results reveal that the investors who display "appetite for information" invest more smartly, i.e. trade funds, execute fewer day trades, are less prone to DE, have more diversified portfolios and ultimately earn higher returns.

This paper makes a valuable contribution to the literature on the relationship between trading behavior and information acquisition. While the vast majority of papers in this strand investigate this topic of research in a purely descriptive way, we base our analysis on the actual trading records of around 14,000 retail investors over the 2008-2012 period. Furthermore, unlike previously published papers, we do not focus solely on trading frequency but analyze trading behavior in a broader sense, including trading performance.

Our findings shed light on two new perspectives that need to be discussed further.

First, the data we have at our disposal does not permit us to disentangle the effect of the distinct feature under study, the "appetite for information", from the effect of the information tool itself. The S-investors may trade differently than the A-investors because of their access to the information tool, meaning that there may be causality issues. While we cannot fully rule out this argument, it seems inconsistent with empirical evidence of how access to more financial information impacts investors' behavior. Notably, Barber and Odean (2001b) report how access to ongoing information has changed the trading behavior of retail investors. These authors suggest that the abundance of financial data, now easily accessible via internet, has encouraged investors to trade more actively by bolstering overconfidence, fueled by an illusion of knowledge and control. In the same vein, Barber and Odean (2002) also report consistent empirical evidence that investors tend to trade more actively and more speculatively after spending time online. Recently, Benamar (2016) has provided evidence that the introduction of a trade order management software (Trade+)[22] by

[22]The aim of the software is to display market data in a more efficient way that simultaneously gather all relevant

a large brokerage house significantly impacted the behavior of individual investors. This author finds that investors started to implement more aggressive trading strategies after the introduction of the software.

Previous papers on this subject have shown that although additional information is a priori useful, it could lead to an illusion of knowledge that make investors believe that they have more abilities to trade than they do in reality. As a consequence, if the difference of trading behavior between the A- and S-investors was due to the information tool itself, we would expect the investors who access the information tool to display more active and aggressive trading strategies and behavioral characteristics that reflect the overconfidence theory. Yet in contrast, the investors who ask for more financial information in our sample make fewer day trades and roundtrips. They also have a larger stock universe and include a higher number of stocks in their portfolios. It also seems unlikely that the information tool under scrutiny is the only explanation for the difference in behavior in complex instruments, since it represents a tool for stocks alone.

There is a second line of discussion about whether the A-investors' decision to forgo the information tool on stocks is not due to a lack of appetite for information but rather because they already have an access to other sources of financial information. However, if the A-investors displayed an appetite for information for other sources of information, it would be unlikely that they would decide against using the information tool provided by the investment firm under scrutiny, as it constitutes an additional (and valuable) means to get informed about the stocks.

In addition, our measure of "appetite for information" may share some characteristics with a personality trait[23] called "openness". Costa Jr and McCrae (1992) define it as the tendency of people to be open-minded and curious. According to personality psychologists, personality traits are key determinants of human behavior (Fung and Durand (2014)). Personality traits have recently been recognized as key variables explaining cross-sectional variations in investors' behavior. Several papers provide evidence that some personality traits are related to trading activity (Lo et al.

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information items (market data, centralized limit order book and investors' orders) into a user-customized screen.

[23]According to Roberts and Mroczek (2008), personality traits are defined as "*the relatively enduring patterns of thoughts, feelings, and behaviors that distinguish individuals from one another*". McCrae and Costa Jr (1997) support that a relatively small set of factors represents the basic dimensions of personality. There is a consensus among psychologists that the "Big Five" personality constructs of Norman (1963) best represents traits structure: (1) Neuroticism (N); (2) Extraversion (E); (3) Openness (O); (4) Agreeableness (A); and (5) Conscientiousness (C).

(2005), Durand et al. (2008), Durand et al. (2013) and Tauni et al. (2015)). According to Costa Jr and McCrae (1992), individuals with high openness have favorable attitudes towards information and welcome it more easily in any context, whether this information has been searched out purposefully or encountered incidentally. These individuals also use imaginative and creative methods to acquire bulk information from a wide variety of sources of information (Kasperson (1978) and Palmer (1991)). Since the investors displaying appetite for information are likely to be open-minded, we consequently do not see any obvious reason why investors who have access to other sources of information would choose to ignore an additional access to stock information.

Finally, our findings have implications for regulators (FED, ECB, ESMA) and investment firms. Our results suggest that the behavior of investors is consistent with the attitude they revealed in the MiFID tests towards financial information. In line with their choice to forgo free access to an information tool, the A-investors trade more intuitively while the investors displaying appetite for information tend to invest more smartly. These findings are also important for assessing the usefulness of the MiFID questionnaire. MiFID questionnaires may contribute to the debate on the financial behavior of individual investors by allowing the identification of investors with an appetite for information. While there is a consensus in the literature that there is a large heterogeneity across retail investors' financial behavior and performance (Barber and Odean (2013)), the important role of some factors has been underlined, namely cognitive capacity (Christelis et al. (2010), Grinblatt et al. (2011)), trust (Guiso et al. (2008)), "sensitivity to the financial thing" (Guiso and Jappelli (2005)), the time spent collecting information (Guiso and Jappelli (2006)), social interactions (Hong et al. (2004)), optimism (Ben Mansour et al. (2006)), financial education (Van Rooij et al. (2011), Lusardi and Mitchell (2014)) or even "happiness" (Kaplanski et al. (2015)). We hope that our findings add a new qualitative determinant to the literature, namely the "appetite for information".

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