Appetite for Information in Mandatory Profiling of Individual Investors

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Abstract

Financial knowledge and the investment in information of retail investors have been under scrutiny both on the side of regulators and of academics. Actually, increasing financial literacy of individuals is one of the promising avenues in order to increase financial markets participation. In this paper, we use a natural field experiment offered by MiFID questionnaires to analyze the relationships between personal traits and trading behavior of retail investors who ask for supplementary information. Under a random matching procedure that controls for socio-demographics, financial experience, education and various survey answers, we analyze the trading characteristics of investors who only differ from others on the side of their "appetite for information". We find that these investors who voluntary ask for more financial information and reveal de facto a particular personality trait tend to behave more consistently with the Traditional Finance theory. Actually, they trade on a larger stock universe, execute less daytrades, are better diversified, and are more active on "complex" instruments. They *in fine* earn higher returns.

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Keywords: information acquisition, personality trait, financial knowledge, MiFID questionnaires

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1 Introduction

In November 2007, the MiFID[1] European Directive came into force. Its goal is to increase the level of protection of 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 so-called "MiFID questionnaires". While the directive requires investment firms to gather relevant information about their clients' profile, the quantity and the nature of the information to be collected depend on the service asked by the retail investor. As illustrated in Figure 1, the Directive determines three types of services (CESR (2008)): Execution of orders, financial advice and portfolio management.

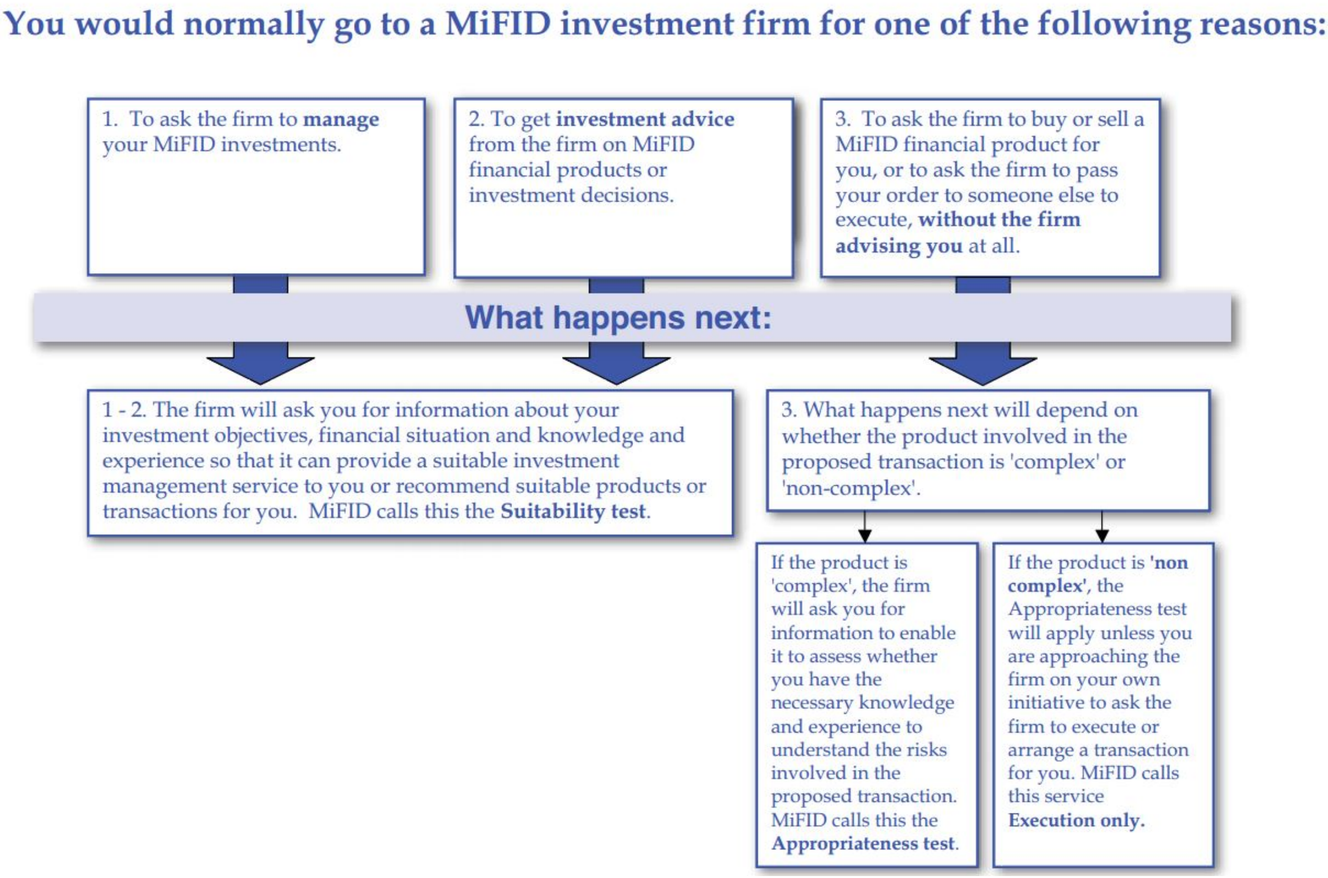
The investors who only ask the banks to execute transactions on "complex" instruments have to fulfill the *Appropriateness test* (hereafter the A-test) that ensures that the customer has the necessary experience and knowledge to understand the risks involved in "complex" financial instruments before investing. However, the investors who ask for financial advice or portfolio management have in addition to fulfill the *Suitability test* (hereafter the S-test). Assessment of suitability involves ensuring that the instruments and services offered meet the investor's objectives, financial capacity as well as his knowledge and experience in financial instruments. Henceforth, MiFID requirements offer a natural field to investigate the relationships between a purposeful need for information, i.e. asking for advice, and the trading behavior of retail investors.

Our paper addresses this topic of research by using a database coming from an online Belgian brokerage house including the MiFID questionnaires records of 14,155 retail investors and their trading activity over the 2008-2012 period. Since our data are provided by an online brokerage house that does not offer any portfolio management service during the sample period, the investors in our sample have either fulfilled the A-test (hereafter A-investors) to execute transactions or fulfilled the A-test and S-test (hereafter S-investors) to have access to an information tool on stocks. Actually, the S-investors have revealed a willingness to access a service higher than orders execution alone ("premium service") bearing the supplementary cost of time needed to fulfill the S-test. By doing so, they have revealed a distinct feature about their personality, that we call "appetite for information". On the contrary, the A-investors

[1] MiFID stands for Markets in Financial Instruments Directive.

have neglected a free access to professional recommendations, suggesting a tendency to exhibit a more "intuitive" trading behavior.

Figure 1: MiFID services



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

Our topic of research belongs to the recent and growing strand of literature on the relationship between personality traits and trading behavior. Besides investors' attributes largely investigated in the literature (e.g. gender, age, income, level of education), personality traits have recently been recognized as key variables explaining cross-sectional variations in investors' behavior. According to personality psychologists, personality is a key determinant of human behavior and performance (Tauni et al. (2015)). Several papers bring effectively evidence that some personality traits are related to trading activity. In a seminal paper, Durand et al. (2008) show that negative emotion is positively related to trading frequency. In a more recent paper, Durand et al. (2013) provide evidence of a negative relationship between extraversion and trading frequency, while their results also suggest that the positive association between agreeableness and conscientiousness is positively related to trading activity. Another study from Tang and Baker (2016) reports that self-esteem, i.e. an individual's general attitude towards oneself (Rosenberg et al. (1995)), is another psychological trait that explains trading behavior. Self-esteem directly or indirectly relates to saving, investment in risky assets and credit management decisions. Finally, Tauni et al. (2015) investigate the association between information acquisition and trading behavior by analyzing the influence of the Big 5 personality traits. They bring evidence that while conscientiousness and extraversion positively moderate the relationship, openness negatively moderates the relationship. Openness is defined by Costa Jr and McCrae (1992) as the tendency of people to be open-minded and curious. As high openness individuals usually have favorable attitudes towards information and welcome it in any context, whether searched out purposefully or encountered incidentally, this trait shares some characteristics with the "appetite for information". High openness individuals use imaginative and creative methods to acquire bulk information from a wide variety of information sources (Kasperson (1978), Palmer (1991)).

Our paper contributes to this literature since the above papers use experiments (i.e. simulated financial markets) or questionnaires administered to a small sample of individuals to investigate the relationship between personality traits and trading frequency. To the best of our knowledge, our paper is one of the first to exploit a large database including the trading records of retail investors over a period of several years to deeply investigate the relationship between a distinct personality trait and trading behavior in a broader sense. Our rich and large database also enables us to investigate to what extent a distinct personality trait, namely the "appetite for information", is related to trading performance, a topic of research that remains under-studied. As far as we know, Lo et al. (2005) and Durand et al. (2008) are the only exceptions. Lo et al. (2005) investigate the relationship between the Big 5 personality traits of 80 daytraders and their performance. Their analysis suggests that there is no significant association between psychological traits derived from a standardized personality inventory survey and trading performance. As for Durand et al. (2008), the authors bring first evidence that personality is related to trading behavior and performance. These authors report that the retail investors who display higher levels of negative emotion, a higher risk taking propensity and a higher openness to experiences are associated to higher portfolio risks. They also show that extraversion, preference for innovation and lower levels of masculinity are positively related to trading performance. However, their study show some limits since they do not have access to actual trading records of the investors under scrutiny. Actually, they asked by mail

21 Australian investors about their portfolio holdings and trades over a one-year period, then re-builded monthly portfolios and computed performance accordingly.

Our paper is also part of the literature on financial information. This strand of literature is characterized by a huge debate concerning the relationship between financial knowledge needs and financial knowledge acquisition. Although some authors argue that financial education is necessary, others suggest that financial advice could be a good solution to 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. In the opposite vein, another approach involves considering financial advice and financial knowledge as complementary (Calcagno and Monticone (2015)). However, our paper differs from those papers since we do not investigate the benefits of financial information *per se* but the impact of the personal characteristics of individuals who voluntary ask (or not) for more useful financial information on their trading behavior. Our aim is therefore to investigate whether the difference of appetite for information between the A- and S-investors lead them to significantly differ in their trading behavior.

Our results indicate that the investors with the highest appetite for useful trading information are the ones who behave more consistently with the Traditional Finance theory. The S-investors effectively trade on a larger stock universe, hold better diversified portfolios, and are more active on "complex" instruments. At the opposite, the more "intuitive" A-investors concentrate their trades on a lower number of stocks, execute more daytrades and roundtrips on this stock set and are less attracted by "other-than-stocks" instruments. This trading behavior difference may explain why the S-investors earn significantly higher returns. This finding holds even under a random matching procedure that controls for socio-demographic data, financial experience, education and various survey answers.

With these results at hand, we also contribute to the literature on the relationship between information acquisition and trading activity. While several papers (a.o Abreu and Mendes (2012) and Tauni et al. (2015)) report empirical[2] evidence of the positive relationship between information acquisition and trading activity, they investigate this relationship only descrip-

[2]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 searching information exceeds its marginal benefit. According to authors (a.o. Grossman and Stiglitz (1980), Karpoff (1986) and Holthausen and Verrecchia (1990)), 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)*".

tively since they do not have trading records but only written answers to surveys.[3] Furthermore, they only focus on trading frequency and dot not analyze trading behavior in a broader sense or even trading performance. To the best of our knowledge, the paper of Guiso and Jappelli (2006) is the only exception. In contrast to Abreu and Mendes (2012) and Tauni et al. (2015), they use a very detailed survey of 1,834 customers of a leading Italian commercial bank to investigate the determinants and the effect of information acquisition on trading behavior and performance. They provide evidence of a negative relationship between information acquisition and returns, supporting the overconfidence hypothesis. Looking at investors' behavior, Guiso and Jappelli (2006) find that information searching is associated to frequent trading, less diversified portfolios and lower tendency to delegate (which confirms their overconfidence evidence).

Besides the fact that we investigate a larger and more recent sample, the difference with the above paper lies in the proxies used to measure investors' attitude towards information acquisition. While Guiso and Jappelli (2006) measure through a questionnaire the time spent for acquiring financial news whatever the source of information (reading the newspapers, surfing on the web, ...), the S-investors in our sample voluntary fulfill the S-test to have an access to a directly usable information tool. Since these investors have produced 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. Two datasets composed the data. The first one contains information about the investors, that we classify into three categories. The first category includes socio-demographic data: year of birth, gender and spoken language. The second category encompasses the answers to the A-test while the third category contains the answers to the S-test. The second dataset is made of detailed information

[3] 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 ask a question like "How often do you buy and sell financial assets?".

about the investors' trading activity on stocks, funds, options, warrants, and bonds. For the purpose of our study, we use information about the stock trading activity to build end-of-month portfolios for each investor in the sample. We complement this dataset with Eurofidai and Bloomberg historical data to compute the market value of the end-of-month portfolios.

2.1 Trading activity

Our sample of investors has made 654,678 trades on 5,959 different stocks,[4] which represents about 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 months trading period.[5] The typical investor makes about 1.4 times daytrading[6] and trades on average 3.37 times the same stock over his whole period of trading. As for the trading activity on "complex" instruments, the average investor completes about 7 trades on investment fund shares, 8 trades on options or warrants and almost no trade on bonds. All the above variables are positively skewed since the means are substantially larger than the medians.

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

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

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

Table 1: Descriptive statistics for trading activity (1)

	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: Descriptive statistics for trading activity (2)

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

The table reports statistics for trading activity built on binary variables. '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.

We use data on the trading activity on stocks and combine it with market data to build end-of-month portfolios. These data allow us to compute the monthly average number of stocks held in portfolio, the monthly average portfolio value as well as the monthly returns.[7]

Table 3 reports descriptive statistics for the above measures. We know that the average investor holds a four-stock portfolio, this underdiversification being in line with 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 Goetzmann and Kumar (2008) who find that more than 50% of the retail investors in their sample hold only one to three stocks. The average end-of-month portfolio value is about 22,000 euros with a median of 6,500 euros. As for the variables reported in Table 1, all these portfolio-based variables are positively skewed.

The average investor earns a monthly gross (net[8]) return of 0.40 (-0.40)% in a typical month.[9] The average monthly volatility of the returns is about 18% with a median of 11.22%. The mean and median volatility are larger that the ones reported in Dorn and Huberman (2005) but the specificity of our sample period may explain the difference.[10] 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.

[7]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)): we assume 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.

[8]Only explicit transactions costs are taken into account.

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

[10]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 on the services they have asked and on the information they have provided accordingly. On the one hand, 6,913 investors have asked the bank to only execute their transactions. These investors have, accordingly to the MiFID Directive, only fulfilled the Appropriateness test (A-investors). On the other hand, 7,242 investors have asked, in addition to the execution of trades, to have an access to an information tool. Therefore they have also fulfilled the Suitability test (S-investors). As a consequence, while both groups execute trades by themselves, the S-investors have a free access to an investment advice tool on stocks. The only "cost" endured to access the information tool is the fulfilling of the S-test. In our case, the S-test under scrutiny is made of 11 questions and covers, in accordance with the MiFID Directive, the investor's objectives, financial capacity as well as his knowledge and experience in financial instruments.

Since both groups have fulfilled the A-test, 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.[11] In addition, we have information about some socio-demographic variables. Table 4 reports for each question the dispersion of the investors between the different categories.

[11] We have grouped some questions when they were related to the same topic. For example, the A-test contains detailed questions regarding the investor's knowledge of options, futures, warrants, structured products,... We have decided to group them and to create a question related to the knowledge of "complex" instruments.

From Table 4, we know that 8.04% of the investors have chosen the highest level when they had to estimate their level of financial markets knowledge. As for the second question, about 5% of the investors have evaluated their experience in options, structured products, forex and futures as “good” while 9.98% as “average” and no experience for the remaining investors. Furthermore, about 34% of the investors have already invested at least once in an option, a structured product, a forex instrument or a future. As for the level of education, 72% have stated to have a university degree or equivalent while 21% a secondary/high school and 6% no degree. A majority of investors are males and speak Dutch. In addition, not reported in the table, the average investor is 44 years old. We finally look at the professional status of the investors and especially at the proportion of executives. In their paper, Bluethgen et al. (2008) and Hackethal et al. (2012) effectively investigate the relationship between executive responsibilities and the demand for financial information. In our sample, about 17% of the investors have stated to be an executive.

Table 4: Statistics for investors' characteristics

	Empirical frequencies
Self-estimated knowledge of financial markets	
Level 0	0.2921
Level 1	0.3099
Level 2	0.3176
Level 3	0.0804
Self-evaluated experience in complex instruments	
Level 0	0.8471
Level 1	0.0998
Level 2	0.0531
Investment in complex instruments	
No	0.6613
Yes	0.3387
Level of education	
Level 0	0.0609
Level 1	0.2149
Level 2	0.7242
Gender	
Female	0.1480
Male	0.8520
Language	
French-speaker	0.4535
Dutch-speaker	0.5077
English-speaker	0.0388
Professional status	
Executive	0.1667
Other	0.8333
N	14,155

The table reports empirical frequencies for investors' characteristics. As 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 any aspect of financial markets. As for the self-evaluated experience in "complex" instruments, level 0, level 1 and level 2 corresponds respectively to 'no experience', an 'average experience' and a 'good experience' in options, structured products, forex and futures. Investment in "complex" instruments is 'yes' if the investor states to have already invested in options, structured products, forex or futures contracts, and 'no' otherwise. As for the level of education, level 0 corresponds to 'no degree', level 1 to a 'secondary school/sigh school degree' and level 3 to a '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 is a French-speaker, 'Dutch-speaker' if the investor is a Dutch-speaker and 'English-speaker' if the investor is an English-speaker. Professional status is 'executive' if the investor claims executive responsibilities and 'other' otherwise.

3 Methodology

The A- and S-investors execute trades by themselves but the S-investors have, in addition, voluntary asked to have an access to superior information. Asides from having fulfilled the A-test, the S-investors have endured the cost of filling in the S-test to have an access to the advice tool. Therefore, they have revealed a particular appetite for information that may have a direct effect on their trading behavior. On the contrary, the A-investors have neglected a free access to more financial information which may reveal a tendency to exhibit a more "intuitive" trading behavior. Our aim is therefore to investigate in a univariate and a multivariate analysis whether the A- and S-investors differ on some of the trading variables presented in Section 2.1.

However, since the investors who ask for more financial information may differ from the others on 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.[12] From the literature, we know that socio-demographic variables (a.o Bluethgen et al. (2008), Haslem (2008) and Gerhardt and Hackethal (2009)), the level of education (a.o Chalmers and Reuter (2010)) and financial literacy (a.o Hackethal et al. (2012), Collins (2012), Georgarakos and Inderst (2014) and Calcagno and Monticone (2015)) are key determinants of the demand for financial advice. As a consequence, a difference in the trading behavior between both groups of investors could be due to other investor-immanent effects that are correlated with the appetite for information.

In this perspective, Table 5 compares the A- and S-investors on the variables displayed in Table 4. Table 5 reports for each categorical variable the proportion by group of investors, the difference between both proportions as well as the significance of the difference. In addition, since we want to compare the trading behavior of each group, any potential difference in trading experience and portfolio value may not be neglected. Glaser (2003), Vissing-Jorgensen (2003) and Abreu and Mendes (2012) report effectively a positive correlation between the size of the portfolio and the trading activity of retail investors. We therefore report by group of investors the monthly average end-of-month portfolio market value and the trading experience as well as the difference between both groups. We also compare the age of each group.

Table 5 clearly suggests that the A- and S-investors significantly differ on the vast majority of the variables. Therefore, to investigate the impact of the appetite for information, the effect

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

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

	A-investors	S-investors	Difference
Self-estimated knowledge of financial markets			
Level 0	0.2930	0.2912	-0.0018
Level 1	0.3101	0.3097	-0.0004
Level 2	0.3072	0.3274	0.0202***
Level 3	0.0897	0.0717	-0.0180***
Self-evaluated experience in complex instruments			
Level 0	0.8277	0.8657	0.038***
Level 1	0.1110	0.0891	-0.0219***
Level 2	0.0613	0.0452	-0.0161***
Investment in complex instruments			
No	0.6708	0.6523	-0.0185**
Yes	0.3292	0.3477	0.0185**
Level of education			
Level 0	0.0703	0.0519	-0.0184***
Level 1	0.2290	0.2015	-0.0275***
Level 2	0.7007	0.7466	0.0459***
Gender			
Female	0.1891	0.1088	-0.0803***
Male	0.8109	0.8912	0.0803***
Language			
French-speaker	0.4762	0.4319	-0.0443***
Dutch-speaker	0.4836	0.5308	0.0472***
English-speaker	0.0402	0.0373	-0.0029
Professional status			
Executive	0.1515	0.1812	0.0297***
Other	0.8485	0.8188	-0.0297***
Age	44.9779	44.6515	-0.3264
Average PF value (in euros)	22,203	21,815	-388
Trading experience (in months)	23.9595	25.5744	1.6149***
N	6,913	7,242	

The table reports for each categorical variable displayed in Table 4 the empirical frequencies of the A- and S-investors. In addition, we report by group of investors the mean of age, the monthly average end-of-month portfolio market value and the trading experience. The last column reports the difference between the A- and S-investors as well as the significance. *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.

of other investor-immanent effects has to be controlled. As stated in Stuart (2010), when estimating causal effects using observational data, it is desirable to replicate experiments as closely as possible by obtaining treated and control groups with similar covariates distributions. As frequently done in the literature (a.o. Gerhardt and Hackethal (2009) and Kramer (2012)), we apply a random matching method using the nearest-neighbor matching algorithm to select a group of "twins" A- and S-investors. According to Stuart (2010), the nearest-neighbor matching is one of the most common and easiest to implement matching method. In its simplest form, 1:1 nearest neighbor matching selects for each treated individual i the control individual with the smallest distance from individual i. The distance between two individuals is based on their respective propensity score that Rosenbaum and Rubin (1983) defines as the probability to receive the treatment given the observed covariates. The propensity score has the advantage to facilitate the construction of matched sets with similar distributions of covariates, without requiring close or exact matches on all of the individual variables (Stuart (2010)).

To compute the propensity score for each investor, we build a logit model where the dependent variable is a binary variable that equals 1 if the investor has asked for an access to the information tool, and 0 otherwise. The independent variables are those reported in Table 5.[13]

Based on the propensity score, since we have more S-investors than A-investors, we associate for each A-investor the "closest" S-investor ("twin" S-investor).[14] In comparison with previous studies, Gerhardt and Hackethal (2009) use gender, age, marital status, risk tolerance, customer experience and deposit value to build comparative subsamples. Kramer (2012) matches on gender, age, residential value, income, portfolio and equity allocation. In contrast to our study, those papers investigate the effect of financial advice on financial behavior. To the best of our knowledge, the only paper that analyzes the effect of financial information acquisition on the trading behavior of retail investors using a similar database is Guiso and Jappelli (2006). While the latter identifies socio-demogaphic variables, wealth, risk tolerance and the level of education as determinants of the search for financial information, they do not apply a random matching.[15] In addition, they do not investigate the effect of financial literacy.

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

[14]Replicating the same methodology by associating for each S-investor a "twin" A-investor provides qualitatively similar results. They are available upon request.

[15]They instead use an instrumental variable approach.

4 Results

4.1 Matching results

Table 6 reports the results of the logit model used to compute the propensity score. By computing the propensity score for each investor, we indirectly highlight the determinants of the appetite for information. Table 6 exhibits parameters estimates as well as significance.

As for financial literacy, the investors who perceive themselves as highly literate and as expert 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 provide evidence that the self-perceived financial literacy is negatively correlated to the demand for financial advice. By contrast, the investors who stated to have effectively invested in "complex" instruments tend to be more information-seeker. While the opposite effect of objective and subjective financial literacy may seem surprising, this result is consistent with Calcagno and Monticone (2015).[16] This finding is a contribution to Guiso and Jappelli (2006) who do not investigate the effect of financial literacy on the tendency to acquire financial information.

As for the level of education, the results suggest that the most educated investors tend to display a higher appetite for information. It is consistent with Hung and Yoong (2010), Collins (2012), Hackethal et al. (2012), and Hoechle et al. (2017) who report that the likelihood to ask for financial advice increases with the level of education. Focusing on the search for financial information, this result is also in line with Guiso and Jappelli (2006). They show that the most educated investors tend to spend more time looking for financial information. According to these authors, the level of education is a proxy for reduced cost of information.

As for the professional status, the investors who claim executive responsibilities tend to display a higher appetite for financial information. It is in contrast with Bluethgen et al. (2008) and Hackethal et al. (2012) who find no effect on the demand for financial advice. Furthermore, masculinity significantly increases the appetite for information, which confirms the result observed in Guiso and Jappelli (2006). However, unlike previous studies, age does not seem to have any significant effect. Finally, the investors having a higher trading experience are more likely to fulfil the S-test and ask for more information. This is to some extent in

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

Table 6: Determinants of the appetite for information

Independent variables	Parameters 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 regression results on the relationship between appetite for information and investors' characteristics. The table reports parameters estimates of a logit model wherein the dependent variable is a binary variable that takes the value 1 if the investor has asked for an access to the information tool on stocks and has accordingly fulfilled the S-test; and 0 otherwise. The set of independent variables includes the variable presented in Table 4. It includes three dummies for the three highest levels of self-estimated knowledge of financial markets, two dummies for the two highest levels of self-evaluated experience in "complex" instruments, a dummy that takes the value 1 if the investor claims to have already invested in "complex" instruments, a dummy that takes the value 1 if the investor states to have a secondary/high school degree, a dummy that takes the value 1 if the investor states to have a university degree, a dummy that takes the value 1 if the investor is a male, a dummy that takes the value 1 if the investor is a French-speaker, a dummy that takes the value 1 if the investor is an English-speaker and a dummy that takes the value 1 if the investor claims executive responsibilities. In addition, the model also includes the age, the natural logarithm of the monthly average end-of-month portfolio market value and the trading experience. *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.

line with Gerhardt and Hackethal (2009) while they show that the investors' ex ante trading experience is positively related to the decision to refer to a financial advisor.

Based on the propensity score, we construct a sample of homogeneous investors using the nearest-neighbor matching method. Since we have associated for each A-investor a "twin" S-investor we end up with a sample of 6,913 A-investors and 6,913 "matched" S-investors.[17] Table 7 provides evidence of the effectiveness of the matching method. Results suggest that "matched" A- and S-investors do not anymore differ. The only exception is the variable related to the second category in the self-evaluated experience in "complex" instruments item (level 1). However the difference is marginally significant (the p-value is equal to 0.0927).

[17]Given that our matching method allows replacement, a S-investor may be matched with two different A-investors.

Table 7: Comparison of investors' characteristics between A- and "matched" S-investors

	A-investors	"matched" S-investors	Difference
Self-estimated knowledge of financial markets			
Level 0	0.2929	0.2983	0.00540
Level 1	0.3101	0.3039	-0.0062
Level 2	0.3072	0.3032	-0.004
Level 3	0.0897	0.0946	0.0049
Self-evaluated experience in complex instruments			
Level 0	0.8277	0.8332	0.0055
Level 1	0.1110	0.1021	-0.0089*
Level 2	0.0613	0.0647	0.0034
Investment in complex instruments			
No	0.6708	0.6679	-0.0029
Yes	0.3292	0.3321	0.0029
Level of education			
Level 0	0.0703	0.0741	0.0038
Level 1	0.2290	0.2366	0.0076
Level 2	0.7007	0.6893	-0.0114
Gender			
Female	0.1891	0.1901	0.001
Male	0.8109	0.8099	-0.001
Language			
French-speaker	0.4762	0.4655	-0.0107
Dutch-speaker	0.4836	0.4953	0.0117
English-speaker	0.0402	0.0392	-0.001
Professional status			
Executive	0.1515	0.1429	-0.0086
Other	0.8485	0.8571	-0.0086
Age (in years)	44.9779	44.8964	0.0815
Average PF value (in euros)	22,203	21,019	-1184
Trading experience (in months)	23.9595	24.0719	0.1124
N	6,913	6,913	

The table reports the comparison between the A- and "matched" S-investors on investors' characteristics presented in Table 4. The last column reports the difference as well as the significance. *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.

4.2 Comparison results

In this section, we compare the A- and S-investors on some of the variables presented in Section 2.1. We first develop a univariate analysis based on mean comparisons and then a multivariate analysis based on regressions.

4.2.1 Univariate analysis

Since the "matched" sample is homogenous, we can compare the trading behavior of the A- and "matched" S-investors in a univariate analysis. Table 8 exhibits for each variable the mean of both groups of investors, the difference between groups as well as the significance of the difference.

The results of Table 8 clearly suggest that the A- and S-investors significantly differ in their trading behavior even after controlling for a large set of investors' characteristics. The differences in the number of daytrades and in the volatility are the only exceptions.

Our results suggest that the S-investors make more trades, but trade on a larger stock universe and make significantly less roundtrips on this set of stocks. In addition, the S-investors tend to hold portfolios including a higher number of stocks. Furthermore, they are more likely to invest in more "complex" instruments, which suggests a higher level of financial sophistication and may indicate a better portfolio diversification.[18] This finding is not in line with Guiso and Jappelli (2006) who report that the most information-seeker investors tend to have less diversified portfolios[19] and tend to invest more in individual stocks. Finally, the S-investors display on average higher monthly gross and net returns than the A-investors. It is still at the opposite of Guiso and Jappelli (2008) who find a negative relationship between information acquisition and returns.

[18] For example, investment fund investing requires first funds screening and then selection according to the investor's profile and needs. In addition, diversifying portfolio through funds requires understanding diversification benefits and the risk related to the assets included in the fund (Guiso and Jappelli (2008)).

[19] These authors use the proportion of the portfolio invested in funds as a proxy for diversification.

Table 8: Univariate comparison results between A- and “matched” S-investors

	A-investors	“matched” S-investors	Difference
Number of stock trades	40.658	48.457	7.799***
Number of daytrades	1.510	1.418	-0.092
Average number of trades on the same stock	3.610	3.150	-0.460***
Number of different stocks traded	10.150	13.040	2.890***
Number of stocks	3.651	4.483	0.832***
Volatility (%)	18.304	19.033	0.728
Proportion of fund traders	0.158	0.258	0.1***
Proportion of option traders	0.170	0.210	0.04***
Proportion of bond traders	0.023	0.037	0.014***
Gross return (%)	0.290	0.650	0.360***
Net return (%)	-0.473	-0.217	0.256***
N	6,913	6,913	

The table reports univariate comparison results between the A- and “matched” S-investors on trading activity variables. The table reports for each variable the mean of both groups of investors, the difference between groups as well as the significance of the difference. ‘Number of stock trades’ is the number of trades executed on stocks. ‘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 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 investment fund traders’ is the proportion of investors who trade at least once investment fund shares. ‘Proportion of option traders’ is the proportion of investors who trade at least once either options or warrants. ‘Proportion of bond traders’ is the proportion of investors who trade at least once bonds. ‘Gross return’ is the geometric average of the monthly gross returns. ‘Net return’ is the geometric average of the monthly net returns. *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.

4.2.2 Multivariate analysis

In the multivariate analysis, we develop 10[20] cross-sectional regressions wherein the dependent variables are the trading variables displayed in Table 8.[21] The set of independent variables includes the control variables included in the logit model (see Table 6) and a dummy equal to 1 if the investor has asked for an access to the advice tool ("S-test" variable), and 0 otherwise.[22] Table 9 reports parameters estimates, significance as well as goodness-of-fit measures.

The results confirm the findings of the univariate analysis. Overall, the parameters estimates of the "S-test" variable are significant and have the expected sign in Regressions (1)-(10). The only differences with the univariate analysis are for the number of daytrades in Regression (2) and for the volatility in Regression (6). In those two regressions, the parameters estimates of the "S-test" variable are significantly negative. In Table 8, the univariate results suggest that the "matched" S-investors do not execute significantly less daytrades than the A-investors although the parameter estimate of the "S-test" variable in Regression (2) indicates now that the appetite for information is associated to a significantly lower number of daytrades. As for volatility, although Table 8 reports no significant difference between the A- and S-investors, Regression (6) reports now that the investors displaying appetite for information hold less volatile portfolios.

Regressions (1)-(10) confirm that the A- and S-investors differ in their trading behavior. Concerning trading activity, the S-investors execute more trades on stocks during their trading period. By contrast, the A-investors trade more frequently on a lower set of stocks. As for diversification, the S-investors tend to hold better diversified portfolios. Their portfolios include effectively a higher number of stocks and are less volatile. In addition, the S-investors seem to be more active on investment funds, options and bonds. Finally, even after controlling for a larger set of variables, the S-investors display a better trading performance.[23]

[20] We do not report the results for the 'Net return' variable. However, they are qualitatively similar to the results for the 'Gross return' variable and are available upon request.

[21] Building on Glaser and Weber (2007), we use the natural logarithm of the continuous variables since these variables are positively skewed. The authors state that this methodology allows to avoid problems of normality, nonlinearity and heteroscedasticity in cross-sectional regressions. For the number of daytrades, we build on Glaser and Weber (2009) and compute the natural logarithm of (1+number of daytrades) since some investors do not make daytrades. In the same vein, we regress the natural logarithm of (1+Gross return) in Regression (10). For Regressions (7) to (9), we develop logit models.

[22] Hung and Yoong (2010) and Hackethal et al. (2012) apply the same procedure to investigate the effect of financial advice on trading behavior.

[23] The result for the 'Net return' variable depicts the same finding even though the parameter estimate is only marginally significant.

The results for the control variables are in line with the extant literature. Our results bring evidence that while masculinity is positively related to trading activity, this attribute is negatively related to performance, which is consistent with the literature on overconfidence (Barber and Odean (2001a)). The results for age is also consistent with the literature. As highlighted in Graham et al. (2009) and Abreu and Mendes (2012), older investors tend to trade less than their younger counterparts. While holding a lower number of stocks, older investors are more prone to hold less volatile portfolios, which is consistent with Dorn and Huberman (2005). Regarding the trading activity on more "complex" instruments, older investors are more likely to invest in funds and bonds but less in options/warrants. Older investors finally earn higher returns, which is consistent with Barber and Odean (2001a). The result for the relationship between the portfolio size and the trading behavior are also in line with the literature. The investors holding larger portfolios display a higher trading activity (a.o. Glaser (2003), Vissing-Jorgensen (2003) and Abreu and Mendes (2012)), regardless the instruments, hold better diversified portfolios (a.o. Dorn and Huberman (2005), Guiso and Jappelli (2008), Goetzmann and Kumar (2008)) and earn higher returns.

All in all, our results suggest that, even after controlling for the self-estimated knowledge of financial markets, the (self-estimated and objective) experience in "complex" instruments, the level of education, socio-demographic variables, the portfolio value and the trading experience, the investors displaying a higher appetite for information tend to display a behavior more in line with the Traditional Finance theory. Indeed, the S-investors tend to hold better diversified portfolios and to display less "aggressive" trading strategies. By contrast, the A-investors tend to be less diversified, to trade on a smaller set of stocks and to be more active on this set of stocks, thereby suggesting a more "intuitive" trading behavior. This type of trading behavior seems to be consistent with the their choice to neglect the access to the information tool. The difference in trading behavior may explain why the S-investors display significantly higher returns. This last finding may seem at odds with papers reporting that financial advice tend to hurt trading performance (a.o. Hoechle et al. (2017)). However, those papers investigate to what extent financial advisors impact returns while we investigate the trading performance of the investors who voluntary ask for a free access to an advice tool on stocks. In this perspective, our results dampen the ones of Guiso and Jappelli (2006) showing that the most information-seeker investors tend to be overconfident and accordingly earn lower returns. The difference in the variable used to measure the investors' attitude towards information acquisition may explain the opposite results. Guiso and Jappelli (2006) measure through a questionnaire the time spent to acquire financial news whatever the source of information (reading the newspapers, surfing on the web, etc). In the questionnaire they use the investors under scrutiny do not give any detail about neither the quality of the source or information nor their application searching for financial information. In our case, the S-investors voluntary fulfill the S-test in order to have an access to a directly usable information tool. Our measure may therefore be more indicative of the investors' appetite for information.

Table 9: Multivariate comparison results

	(1) Ln(n_trades)	(2) Ln(1+n_Dt)	(3) Ln(same_stock_t)	(4) Ln(n_stocks)	(5) Ln(stocks_PF)	(6) Ln(volat)	(7) F_trader	(8) O_trader	(9) B_trader	(10) Ln(1+g_r)
Intercept	-1.001***	-0.367***	0.807***	-1.304***	-2.468***	2.674***	-3.774***	-3.899***	-7.553***	-0.012***
S-test	0.141***	-0.0256**	-0.075***	0.237***	0.214***	-0.070***	0.679***	0.152***	0.548***	0.002***
Self-estimated knowledge of financial markets 1	-0.082***	-0.048***	-0.061***	-0.002	-0.013	-0.030*	0.161***	0.161**	0.158	-0.001
Self-estimated knowledge of financial markets 2	-0.102***	-0.078***	-0.080***	0.004	-0.046***	-0.068***	0.426***	0.653***	0.565***	0.001
Self-estimated knowledge of financial markets 3	-0.143***	-0.055*	-0.055***	-0.073**	-0.202***	-0.053*	0.571***	1.244***	0.769***	-0.001
Self-evaluated experience in complex instruments 1	0.104***	0.116***	0.075***	0.001	-0.098***	0.102***	-0.016	0.081	-0.181	-0.001
Self-evaluated experience in complex instruments 2	0.123***	0.112***	0.058***	0.004	-0.115***	0.122***	-0.065	0.397***	0.024	0.001
Investment in complex instruments "Yes"	-0.018	-0.019	-0.010	-0.006	-0.017	0.015	0.231***	0.728***	0.356***	0.003***
Level of education 1	0.035	-0.044	-0.006	0.039	0.053*	0.001	0.029	-0.069	-0.405*	-0.003
Level of education 2	-0.178***	-0.154***	-0.086***	-0.065**	0.073***	-0.086***	0.263**	-0.141	-0.201	-0.001
Male	0.162***	0.086***	0.065***	0.075	0.001	0.0254	-0.042	0.053	-0.161	-0.002*
French-speaker	0.112***	0.142***	0.087***	-0.003	-0.144***	0.034***	-0.101**	0.344***	-0.118	-0.001
English-speaker	-0.169***	-0.002	0.012	-0.181***	-0.209***	-0.037	0.113	0.091	-0.381	0.002
Executive	-0.153***	-0.096***	-0.043***	-0.092***	-0.009	-0.033**	0.119**	-0.188***	-0.213	0.001
Age	-0.006***	-0.004***	-0.002***	-0.002***	-0.001***	-0.001**	0.008***	-0.001***	0.024***	0.001***
Ln(PF value)	0.384***	0.083***	0.061***	0.305***	0.369***	-0.021***	0.093***	0.136***	0.189***	0.001***
Trading experience (in months)	0.034***	0.008***	0.007***	0.024***	0.011***	0.008***	0.0163***	0.028***	0.033***	-0.001***
Adjusted r^2	43.73%	7.40%	10.98%	43.16%	44.04%	3.04%	-	-	-	0.79%
Pseudo r^2	-	-	-	-	-	-	5.36%	10.35%	8.50%	-
N	14,155	14,155	14,155	14,155	14,155	14,155	14,155	14,155	14,155	14,155

The table reports regression results on the relationship between trading activity variables and the appetite for information. The dependent variables of Regressions (1) to (10) refer to the trading activity variables presented in Table 8 and are the natural logarithm of the number of stock trades, (1+ the number of daytrades), the average number of trades on the same stock, the number of different stocks traded during the whole trading period, the monthly average number of stocks held in portfolio, the volatility, a dummy that takes the value 1 if the investor trades investment fund shares at least once, a dummy that takes the value 1 if the investor trades either options or warrants at least once, a dummy that takes the value 1 if the investor trades bonds at least once and the natural logarithm of (1+the geometric average of the monthly gross returns). The set of independent variables includes a dummy ('S-test') that takes the value 1 if the investor has asked for an access to the information tool on stocks and has accordingly fulfilled the S-test. It also includes control variables as in Table 6. It includes three dummies for the three highest levels of self-estimated knowledge of financial markets, two dummies for the two highest levels of self-evaluated experience in "complex" instruments, a dummy that takes the value 1 if the investor claims to have already invested in "complex" instruments, a dummy that takes the value 1 if the investor states to have a secondary/high school degree, a dummy that takes the value 1 if the investor states to have a university degree, a dummy that takes the value 1 if the investor is a male, a dummy that takes the value 1 if the investor is a French-speaker, a dummy that takes the value 1 if the investor is an English-speaker, a dummy that takes the value 1 if the investor claims executive responsibilities, age, the natural logarithm of the monthly average end-of-month portfolio market value and the trading experience. *** indicates significance at 1%; ** indicates significance at 5%; * indicates significance at 10%.

5 Conclusion

Over the last decade, financial market participation by retail investors has regularly decreased, which has constituted a major issue for policymakers and regulators. In order to reintroduce confidence, they have developed new rules that aim at protecting individual investors. The Markets in Financial Instruments Directive fits this objective as it renders mandatory for investment firms operating in the EU to collect information about their retail clients through the MiFID tests. Depending on the services offered by the institution, clients have different levels of questions to answer. Our data allows 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 personality trait, that we call "appetite for information", trade differently than the investors neglecting an access to additional financial information. We find that the investors who display "appetite for information" trade funds, do less daytrades, are better diversified and *in fine* earn higher returns, others trading and personal characteristics being controlled.

Recent literature focuses on factors that appear to play an important role in terms of participation in the stock market as well as financial behavior: 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)). Our paper adds a new determinant, namely the "appetite for information".

As for academia, our paper contributes to two strands of the literature: (a) The literature on the relationship between trading behavior and information acquisition and (b) The literature on the relationship between trading behavior and personality traits. While the vast majority of papers in both strands investigate these topics of research only descriptively (Tauni et al. (2015)), we base our analysis on actual trading records of about 14,000 retail investors over the 2008-2012 period. Furthermore, unlike precedent papers, we do not focus on trading frequency only but analyze trading behavior in a broader sense, including trading performance.

Our findings have also implications for regulators (FED, ESMA, AMF) and investment firms. Our results suggest effectively that investors' behavior is consistent with their attitude towards financial information. In line with their choice to neglect a free access to an information tool, the A-investors trade more intuitively while the investors displaying appetite for information tend to behave more consistently with the Traditional Finance theory.

Our paper has nevertheless an important drawback. With those data at hand, we are not able to disentangle the effect of the distinct personality trait 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. While we cannot fully rule out this argument, it seems inconsistent with empirical evidence showing how access to more financial information impacts investors' behavior. In their overview of the relationship between the investor and the internet, Barber and Odean (2001b) report how the access to ongoing information thanks to the internet has changed the trading behavior of retail investors. These authors suggest that abundant financial data, now easily accessible through the internet, has encouraged investors to trade more actively by bolstering overconfidence, fueled by an illusion of knowledge and control (Barber and Odean (2002)). While a priori useful, these authors warn that additional information could lead to an illusion of knowledge that make investors believe that they have more abilities to perform tasks such as stock-picking.

Barber and Odean (2002) report consistent empirical evidence showing that after going online, investors tend to trade more actively and more speculatively. In the same vein, Benamar (2016) brings evidence that the introduction by a large brokerage house of a trade order management software (Trade+)[24] has significantly impacted the behavior of individual investors. This author finds that, after the introduction of this software, the investors under scrutiny have started to implement more aggressive trading strategies allowed by a better monitoring of short-term trading strategies. He effectively shows that the number of short-term trading strategies (short-term round-trips and daytrades) has increased for the investors who opted for this tool.

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 get an access to the information tool to display more active and aggressive trading strategies as well as behaviorial characteristics in line with the overconfidence theory. However, the behavior of the S-investors under study is at odds with such a theory. According to Odean (1998), overconfident investors trade more actively and more speculatively than they otherwise would, and hold underdiversified portfolios. By contrast, the investors who ask for more financial information in our sample

[24]The aim of the software is to display market data in a more efficient way that simultaneously gather all relevant information items (market data, centralized limit order book and investors' orders) into a user-customized screen

make less daytrades and less roundtrips. They also have a larger stock universe and include a higher number of stocks in their portfolios. It is rather the A-investors who display personality traits in line with the overconfidence theory. In addition, it seems unlikely that the information tool under scrutiny explains by itself the difference in behavior in complex instruments since it represents a tool on stocks only.

Another drawback comes from the fact that the A-investors may decide to neglect the information tool on stocks, not because of a lack of appetite for information but because they already have an access to other sources of financial information. However, if the A-investors displayed appetite for information for other sources of information, it would be unlikely that they decide not to use the information tool provided by the investment firm under scrutiny. Indeed, this tool constitutes an additional (and valuable) means to get informed about the stocks. In this paper, we consider the appetite for information as a personality trait that is close to another one called "openness". Costa Jr and McCrae (1992) suggest that 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. We accordingly do not see any obvious reason that the investors showing high appetite for information could choose to neglect an additional access to information about stocks even if they had access to other sources of information.

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