Investor sentiment and stock return predictability: The power of ignorance*

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Abstract

A number of papers show that investor sentiment measures based on the market activity of retail investors carry some predictive power of future market returns. In this paper, we use such a sentiment measure on two samples of approximately 25,000 individual investors, who differ by their appetite for information and professional recommendations. Our data cover 51 months from January 2008 to March 2012. We show that the sentiment of investors who neglect either free information or professional advice has more power in predicting future returns than the sentiment of investors who access to more information and recommendations. Our findings remain valid when controlling for investor characteristics like spoken language (French or Dutch), for investor portfolio value, and for investor self-reported financial literacy. Our results suggest that market sentiment essentially refers to the fast and automatic System-1 reasoning. When shared by many investors, sentiment can generate long-lived mispricing that is therefore difficult to arbitrage.

Keywords: Investor sentiment, underdiversification, information seeking, recommendations, retail investors

JEL Classification: G02, G11, G28

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1 Introduction

In the 80s, retail investors were often identified as noise traders because "they trade on noise as if it were information"(Black, 1986). If markets were efficient, it would mean that noise traders do not influence prices. But since the end of the 90s, an abundant literature on retail investors has developed, notably initiated by Terrance Odean (1998, 1999). The main stylized facts in this literature state that 1) retail investors hold underdiversified portfolios, 2) retail investors frame narrowly their decisions, and 3) their trades are correlated.

The first stylized fact, i.e. retail investors hold underdiversified portfolios, is highlighted in Lease, Lewellen, and Schlarbaum (1974) and Blume and Friend (1975). More recent studies confirm that retail investors hold largely underdiversified portfolios (Kelly, 1995; Odean, 1999; Kumar, 2007; Goetzmann and Kumar, 2008; Mitton and Vorkink, 2007; Broihanne, Merli, and Roger, 2016), containing less than five stocks on average. From a theoretical point of view, investors' desire to hold positively skewed portfolios (Barberis and Huang, 2008; Brunnermeier, Gollier, and Parker, 2007; Brunnermeier and Parker, 2005) or investors' solvency constraints (Liu, 2014) may justify such an underdiversification.

The second stylized fact, i.e. narrow framing, means that retail investors evaluate stocks in isolation (Barberis, Huang, and Thaler, 2006). Contrary to the assumptions of both expected utility theory and Markowitz portfolio choice theory, retail investors do not consider their portfolio as a whole. Their decisions to buy or sell a given stock are motivated by their expectations for this stock, which is optimism/pessimism about the future return on this specific stock. Narrow framing is accentuated when investors' portfolios contain a very low number of different stocks (Kumar and Lim, 2008).

The third stylized fact, i.e. correlated trading, implies that suboptimal diversification choices of retail investors can move stock prices and partly drive future returns, as illustrated in Dorn, Huberman, and Sengmueller (2008). Using a sample of 37,000 clients of a German broker, these authors show that trades of retail investors are systematically correlated. They also find that correlated limit orders have some predictive power of subsequent market returns. In addition, Kumar and Lee (2006) show that stocks with high retail concentration comove more together than they comove with other stocks.

Considering the three stylized facts together, it turns out that correlated trading by underdiversified and narrowly framed investors can generate persistent mispricing. This makes the construction of a sentiment index that can have a significant predictive power of future returns on specific portfolios especially relevant. In fact, the trading behavior and the portfolio dynamics of retail investors are good signals to measure the (excessive) optimism/pessimism of market participants. Optimism/pessimism of investors is often translated in terms of investor sentiment, which is defined by Baker and Wurgler (2007) as "a belief about future cash flows and investment risks that is not justified by the facts at hand".

With the words of Kahneman (2011), sentiment investors think more with their System 1 (fast and automatic) than with their System 2 (slow and effortful) when they decide to purchase a stock. Roughly speaking, the brain of a decision maker typically uses two mental systems, named System 1 and System 2. System 1 is automatic, affective and heuristic-based. It is the way of thinking that allows us to tell immediately if someone is angry, after seeing her facial expression. By contrast, System 2 requires effort and is mainly rule-based. We use it when computing, for example, the product of 13 and 52. When faced with a decision, System 1 makes immediately an assessment based on a first impression, and transfers this assessment to System 2. System 2 either accepts the System 1's assessment or modifies it more or less. Research on decision-making shows that System 2 often accepts the suggestion of System 1 or adjusts it only slightly. Hence, System 1 has a strong impact on most of our decisions, including our financial decisions. The problem is that System 1 is an associative machine. It is able to construct the best story that incorporates available information, but it will not warn you that some information is missing and that you should look for more information. Kahneman (2011) summarizes this situation as follows : "The measure of success of System 1 is the coherence of the story it manages to create. The amount and quality of data are largely irrelevant... System 1 operates as a machine for jumping to conclusions."In the same vein, Barberis, Mukherjee, and Wang (2014) argue that "first impressions"are important in the decision-making process of retail investors.

When sentiment/retail investors trade in concert and generate a non negligible part of the trades, it becomes costly and risky for rational arbitrageurs to bet against sentiment investors (Shleifer and Vishny, 1997). An obvious consequence is a potential mispricing.

The Internet bubble at the end of the 90s is the typical example of this kind of situation where euphoria contaminates investors' decisions and prevents rational arbitrageurs to correct price trajectories.[1]

This paper is based on two building blocks related to the above literature. First, investor sentiment measures often rely more or less explicitly on the behavior of retail investors. In short, a measure of sentiment that scores high (low) is an indicator of excessive optimism (pessimism) among retail investors. Future returns are therefore expected to be low (high). Second, sentiment is essentially driven by System 1 thinking. As a result, we expect that a sentiment indicator built on the behavior of investors who 1) do not use professional recommendations and 2) do not look for (free) additional information, is a better predictor of future returns than the same indicator built on the behavior of investors more eager to collect information and to use professional advice.

As shown by Baker and Wurgler (2007), small caps are more influenced by sentiment than large caps. A good sentiment index should then have some explanatory power of the future returns on a long-short portfolio based on size. The market sentiment index (MSI henceforth) used in this paper was developed by Roger (2014). This author shows that the MSI performs better than a number of other sentiment indices in predicting future returns on long-short portfolios based on size.

The MSI is based on the dynamics of portfolio diversification of retail investors. The intuition behind this indicator is very simple: when a retail investor, who holds a small number of different stocks in his/her portfolio (for example, 2 or 3), decides to buy a new stock, his/her main motivation is that he/she is optimistic about the future returns on this stock (typical narrow framing). When a lot of underdiversified retail investors increase (decrease) the number of different stocks in their portfolios, they are optimistic (pessimistic) about future returns and sentiment is high(low).

The MSI has several advantages. First, it can be calculated with any sample of retail investors' portfolios. Second, computing the indicator at a given date t only requires the transition matrix of the process N_t of the number of different stocks in investors' portfolios at date t.[2] Third, the MSI is not contaminated by liquidity considerations.

[1] Moreover, Baker, Pan, and Wurgler (2012) show that sentiment is contagious across countries.

[2] One of the most popular sentiment indices is the one built by Baker and Wurgler (2006). Their index is a linear combination of six variables known to be influenced by the optimism/pessimism of investors: the closed-end fund discount, the logarithm of the NYSE share turnover ratio (detrended by the 5-year moving average), the number of IPOs, the average first-day return on IPOs, the share of equity issues

The second building block of this paper is a proprietary database of 45,085 retail investors' online accounts. First, we have all the investors' trading activity over the period from January 2008 to March 2012. Second, we have the investors' answers to both the Suitability test and the Appropriateness test, which are imposed in EU member states since the implementation of MiFID in November 2007. In a nutshell, MiFID requires investment firms to submit questionnaires to their clients in order to determine their financial capacity, their financial experience and knowledge, and their investment objectives. Such tests should help firms offer retail investors suitable services. In particular, a *suitability* assessment is required before providing investment advice or portfolio management services while an *appropriateness* assessment is required before providing only execution and transmission of orders on complex instruments. Using the information available on the MiFID tests, we are able to distinguish A-investors, i.e investors who only filled in the *Appropriateness* test, and S-investors, i.e. investors who filled in both the *Appropriateness* test and the *Suitability* test. Specifically, we consider the Suitability test as a proxy for the investor's appetite for information and professional advice.[3] Since the access to the investment advice tool on the web platform is free (the only cost is to fill in the questionnaire), A-investors neglect free information and professional advice, compared to S-investors. We conjecture that A-investors are more prone to sentiment trading than S-investors. As a consequence, we expect that a sentiment indicator built with the portfolio dynamics of A-investors (S-investors) has a stronger (weaker) predictive power of future returns on a long-short portfolio based on size.

Our results confirm our expectations. The MSI is especially effective when it is based on the subsample of A-investors who report a low level of financial literacy. Moreover, the MSI predictive power becomes even stronger if we isolate the peculiarity of A-investors with respect to S-investors, i.e. using as a predictor of returns the residual of the regression of the MSI of A-investors on the MSI of S-investors. Our results are robust to a propensity score matching procedure aimed at neutralizing spoken language, wealth and financial literacy.

The paper is organized as follows. Section 2 shortly presents the MSI and its main

in total equity and debt issues and the dividend premium, defined as the log difference in the average market-to-book ratios between dividend payers and non-payers. The sentiment measure is chosen as the first principal component of a Principal Component Analysis of the six variables.

[3]Over the sample period, the brokerage house was not offering portfolio management services to its clients.

properties.[4] Section 3 describes our data and provides some descriptive statistics. Section 4 presents the empirical results and section 5 develops robustness checks. Section 6 concludes.

2 The market sentiment index

As mentioned earlier, the MSI is built on the stylized facts that spring from both the underdiversification of retail investors' portfolios and the narrow framing of these investors (Roger (2014)). The MSI is well-suited to our data because its construction only needs the time series of the number of different stocks held in investors' portfolios. We briefly summarize hereafter the formal definition and the properties of the index. The main mathematical tools of this construction are the properties of Markov chains.

2.1 The Markov chain of diversification levels

Assume that K stocks are traded in the market by a set of I investors over time-periods numbered from 1 to T. N_t is the number of different stocks held by an investor at date t. N_t is a random variable taking values in the set $\{0, ..., K\}$.

Let Q_t stands for the one-period transition probability matrix of the stochastic process $(N_t, t = 0, ..., T)$. It is defined by:

$$\forall 1 \leq k \leq K, \forall 1 \leq m \leq K, Q_t(k, m) = P(N_{t+1} = m \,|N_t = k) \tag{1}$$

$Q_t(k, m)$ is the probability that the portfolio contains m different stocks at date $t+1$, knowing that it contained k different stocks at date t. In the empirical part, we assume that $K = 5$ because most of the investors in our sample hold less than 5 stocks (state K receives then all portfolios with a number of different stocks greater than or equal to K). The elements of Q_t located above the diagonal are greater than those below the diagonal when investors have a tendency to increase the number of different stocks in their portfolios. Portfolios become more concentrated when the opposite is true. We should notice that neither the trading volume nor the stock price enter the calculation of our sentiment index.

[4] See Roger (2014) for the technical details.

2.2 Formal definition of the MSI

If the structure of Q_t signals the sentiment of investors between dates t and $t+1$, and is stable over time, the properties of homogeneous Markov chains[5] tell us what happens to the long-term transition matrix which is $Q_\infty = lim_{n\to\infty} Q_t^n$. In fact, all lines of Q_∞ are equal to the equilibrium distribution of the number of stocks in portfolios, denoted $N_{\infty,t}$. Roger (2014) defines the MSI as the area below the decumulative distribution function of $N_{\infty,t}$. The intuition is that if investors are optimistic and buy new stocks, the structure of Q_t leads to an equilibrium probability distribution of N_∞ that overweights large values of $N_{\infty,t}$. As a consequence, the area above (below) the cumulative (decumulative) distribution of $N_{\infty,t}$ is large (small).

MSI_t is formally defined by:

$$MSI_t = \frac{1}{K-1} \sum\nolimits_{k=1}^{K-1} P(N_{\infty,t} > k) \tag{2}$$

An essential feature of the convergence theorem of Markov chains is that the steady-state equilibrium does not depend on the initial distribution of investors. It turns out that only the changes between $t-1$ and t are important.

Q_t contains useful information about the dynamics of portfolio diversification. During long bullish high-sentiment periods (such as the dotcom bubble), more and more investors enter the market and those already in the market increase their stakes and invest in new stocks, thus increasing diversification.[6]

Roughly speaking, $Q_t\,(k,m) > Q_t(m,k)$ in bullish markets. In bearish markets or recession periods, investors are reluctant to put new money on the table and may sell stocks to finance consumption or because of liquidity needs. Consequently, we expect $Q_t\,(k,m) \leq Q_t(m,k)$ in bearish markets.[7]

The mechanics driving the Markov chain is then clearly linked to the optimism/pessimism of the retail investors, assuming that their portfolios are underdiversified and that they

[5] A Markov chain is said homogeneous if Q_t does not depend on t.

[6] Goetzmann and Kumar (2008) note an increase in the mean number of stocks in retail investors' portfolios from 4.28 in 1991 to 6.51 in 1996. In such cases, the elements above the diagonal of the transition matrix increase over time.

[7] However, some asymmetry may arise due to the disposition effect. As a consequence, reluctance to sell stocks in bearish markets can induce some inertia in Q_t. It turns out that the time-series of the terms on the diagonal of Q may be a relevant measure of pessimism.

narrowly frame their decisions.

3 Data and descriptive statistics

The data on individual investors come from a large online Belgian brokerage house. Our study covers the period from January 2008 to March 2012 and is based on 45,085 retail investors, who completed 2,333,372 trades across 9,064 different stocks. Two types of information are available in this proprietary database[8]. The first dataset provides detailed information about each trade, i.e. the ISIN code of the instrument, the time-stamp, the trade direction, the executed quantity and the trade price. We also know the currency in which the trade is executed, which allows us to compute the traded volume in euros.[9] The online brokerage house provides retail investors with an access to a large panel of financial instruments. The main traded securities are stocks, funds, options, warrants, and bonds.[10] The second dataset contains additional information about the investors: socio-demographic characteristics such as the year of birth, the gender and the spoken language,[11] but also their answers to the MiFID tests.

MiFID[12] came into force in November 2007 across the EU member states. One of its objectives was to increase the level of protection of investment firms' retail clients. Accordingly, MiFID requires investment firms to submit questionnaires to their clients in order to determine their financial capacity, their financial experience and knowledge, and their investment objectives. Such tests should help firms offer retail investors suitable services. In particular, a *suitability* assessment is required before providing investment advice or portfolio management services while an *appropriateness* assessment is required before providing only execution and transmission of orders on complex instruments. The way to assess suitability and appropriateness is however not constrained and each investment firm is free to devise and organize its own questionnaire(s) provided it abides by

[8]Each investor is anonymized but registered with a unique code allowing us to select all information relative to any specific investor

[9]When necessary, we use historical exchange rates from the European Central Bank to convert monetary volumes into euros.

[10]Only futures cannot be directly traded on the common trading platform. As a result, we do not have data about the trading activity on futures.

[11]Belgium has three official languages : French, Dutch and German. French and Dutch are the most spoken. On the online trading platform, investors can choose among the three available languages: French, Dutch or English.

[12]We refer here to MiFID I (2004/39/EC). MiFID II (2014/65/UE) will come into force in January 2018 and then will replace the first version of this directive.

some general guidelines.

In our case, the brokerage house made use of two distinct questionnaires for appropriateness and suitability. Assessment of appropriateness mainly requires ensuring that the investor has the necessary experience and knowledge to understand the risks involved in complex financial instruments. In practice, the brokerage house has implemented a specific Appropriateness test (A-test henceforth) for an exhaustive list of instruments, including shares traded on a non-European market or on a European non-regulated market.[13] As a result, all the retail investors in our sample provided answers to this A-test, i.e. 45,085 individuals. Over the sample period, the brokerage house was providing its clients with a free access (through the web platform) to an investment advice tool on stocks (which delivers more detailed information on stocks and professional recommendations) while it was not offering portfolio management services. To get access to this advice tool, investors have to fill in the Suitability test (S-test henceforth). In our sample, only 21,738 investors decided to fill in this S-test.

Using the information available on the MiFID tests, we are able to distinguish A-investors, i.e investors who only filled in the A-test, and S-investors, i.e. investors who filled in both A-test and S-test. Specifically, we consider the S-test as a proxy for the investor's appetite for information and professional advice. Since the access to the investment advice tool on the web platform is free (the only cost is to fill in the questionnaire), A-investors neglect free information and professional advice, compared to S-investors.

Over the 51-month period, we count for S-investors 1,312,519 trades on stocks, whose 58% are purchases. For A-investors, we have 1,020,853 trades on stocks, with 57% of them that are purchases. In monetary volumes, S-investors (A-investors) trade about €10,065 millions (€9,268 millions), with 52% (51%) of that amount for purchases. For the purpose of our study, we focus on stocks and use information about trading activity to build end-of-month portfolios for each investor. With these data at hand, we compute the monthly average number of stocks held in portfolio as well as the monthly average portfolio value. For daily stock prices and European Fama-French factors, we use two additional sources: Eurofidai[14] and Bloomberg. We also measure the monthly average turnover as well as both gross and net monthly returns of each investor's stock portfolio.

[13]Such as Multilateral Trading Facilities under the MiFID typology.
[14]www.eurofidai.org

Insert Table 1 here

Table 1 reports cross-sectional statistics for the investors' trading activity. Trade-based measures in Panel A show that S-investors execute more trades than A-investors. This is valid for all the instruments (stocks, options, funds, and bonds). S-investors also exhibit a longer trading experience: about 28 months on average in comparison with about 22 months on average for A-investors. In addition, S-investors trade more frequently than A-investors, i.e. the number of days between two consecutive trades on stocks is smaller for them. In Panel B, the stock portfolio-based variables are consistent with the portfolio underdiversification documented in the literature for retail investors. On average, A-investors hold a three-stock portfolio while S-investors hold a six-stock portfolio. This difference is significant at the 1% level and is still valid when we look at the medians that are smaller (1.84 for A-investors and 3 for S-investors). These figures reveal that A-investors hold more underdiversified portfolios than S-investors. When we consider the portfolio value, S-investors hold larger portfolios than A-investors: the monthly average portfolio value is €48,477 for S-investors and €36,956 for A-investors. For both types of investors, the monthly portfolio values are however positively skewed since the mean value is much larger than the corresponding upper quartile value. This suggests a large dispersion for portfolio value in both sub-samples. As for the value by position, we do not observe a statistical difference between the monthly averages, although the medians differs and show a slightly larger value by position for S-investors (€1,727 against €1,575). The monthly average turnover is equal to 4.11 for A-investors and to 1.81 for S-investors. The difference is statistically significant at the 10% level and suggests that A-investors churn on average more frequently their portfolio than S-investors. In Panel C, we observe that A-investors earn on average a slightly higher monthly return than S-investors. All in all, S-investors appear to be more sophisticated (or experienced) investors than A-investors. Nevertheless, this apparent higher sophistication (experience) does not lead to a better monthly performance. This observation is consistent with Hoechle, Ruenzi, Schaub, and Schmid (2016) who show that professional advice hurts the retail investors' portfolio performance.

Insert Table 2 here

Table 2 reports some demographics about the investors. The median age is very close in both sub-samples, i.e. 47 versus 48 years old. 18% of A-investors are female while we count only 10% of females for S-investors. As for the spoken language, Dutch-speaking investors have a small majority in both sub-samples (55% or 56%). When we look at the education level, the proportion of investors who report they hold an university degree or an equivalent is larger for S-investors (73% in comparison with 67%).

Insert Table 3 here

Statistics for the self-reported financial literacy are provided in Table 3. For both A-investors and S-investors, we observe a real dispersion across the four levels proposed on the scale. The proportions mainly differ between A-investors and S-investors for the levels 0 and 2. A larger proportion of A-investors report a basic knowledge (28% of A-investors versus 22% of S-investors). By contrast, a larger proportion of S-investors select the third level on the scale, which states that the investor "understands the functioning of the financial markets and knows that the fluctuations can be important and that the various sectors and categories of products have different characteristics relating to their revenue, growth and risk profile"(40% of S-investors versus 32% of A-investors). These differences show that S-investors tend to self-report a higher financial literacy.

4 Empirical results

4.1 Correlation analysis

Baker and Wurgler (2007) introduce the "sentiment seesaw"to explain the effect of sentiment on stocks (figure 1, p133). They show that sentiment can have opposite effects on stock returns, depending on the difficulty of engaging in arbitrage. In high-sentiment periods, stocks that are easy to arbitrage (large stocks in particular) may be undervalued and stocks that are difficult to arbitrage (small stocks) may be overvalued. The reverse appears in low-sentiment periods. As a consequence, we expect small caps to be overvalued in comparison with large caps in high-sentiment periods, the reverse being expected in low-sentiment periods. If this prediction is true, small stocks should have low (high) returns following a high-(low-)sentiment period. A good sentiment measure should help to forecast future returns. In addition, a good sentiment index is expected to be more correlated to future returns on small stocks than on large stocks.

We first calculate the sentiment index for the whole sample (MSI) and for the two subsamples. $AMSI$ ($SMSI$) denotes the sentiment index calculated with the subsample of A-investors (S-investors). As we are mainly interested by the difference between S-investors and A-investors, we denote RES the residual of the regression of $AMSI$ on $SMSI$. Our conjecture is that RES should be a good sentiment indicator because it extracts the specificity of A-investors who voluntarily base their decisions on less information and without professional advice. It is likely that these investors are either more overconfident or more driven by their System 1(Barberis, Mukherjee, and Wang, 2016).

Table 4 provides the correlations between the four market sentiment variables ($AMSI$, $SMSI$, MSI, RES) and the economic variables and risk factors, mainly the four Fama-French-Carhart factors: market premium (MKT), size (SMB), book-to-market (HML), momentum (MOM). We also consider the returns on three size-based portfolios. *Lcaps* (*Mcaps* and *Scaps*) is the return on the value-weighted portfolio built with the tercile of large caps (mid-caps and small caps).[15] The last variable $Small - Big$ is the return on the long-short portfolio, which is of particular interest in our study. As usual, this portfolio is long on small caps and short on large caps. Table 4 contains two panels. Panel A(B) shows contemporaneous (lagged) correlations. For example, the first figure of Panel A is -0.354, which is the empirical correlation between $SMSI_t, t = 1, ...T$ and $MKT_t, t = 1, ...T$ where $t = 1$ corresponds to January 2008 and T to March 2012. The first figure of panel B is -0.063, which is the correlation between $SMSI_t, t = 1, ...T - 1$ and $MKT_t, t = 2, ...T$.

Insert Table 4 here

Panel A of Table 4 shows significant negative contemporaneous correlations between our sentiment measures and portfolio returns. These negative correlations can be interpreted in several ways but are consistent with the disposition effect documented in the literature on retail investors. When prices drop, retail investors tend to keep their losing stocks, or, even worse, to buy new stocks in order to decrease the average buying price. On the up-side, the disposition effect leads people to sell their stocks too early after a price increase. These sales generate a decrease in the sentiment index value. The correlations in columns 1 and 5 to 7 are thus compatible with this usual interpretation.

[15] The returns on the three size-based portfolios are directly provided by Eurofidai. These portfolios are the three terciles of the universe of European stocks in the database.

Another interesting observation is that correlations in the last column are positive, even if they are insignificant. This positive sign is compatible with the interpretation that the more investors are optimistic, the more they prefer small stocks, leading to a higher return on small stocks than on large stocks. However, given the insignificance of the correlations, we cannot conclude to a contemporaneous relationship between the return on the long-short portfolio and the sentiment index. Consistent with this remark is the absence of significant correlation between the sentiment measures and the size factor.

The results are different for lagged correlations in Panel B. We observe a difference between large caps and small caps,[16] resulting in significant correlations between $AMSI$ or RES and the long-short portfolio return. On the contrary, the sentiment measure based on S-investors ($SMSI$) is correlated neither with future returns on the size-based portfolio nor with the Fama-French-Carhart factors. Table 4 reveals therefore differences between sentiment calculated with the portfolio dynamics of well-informed investors using professional recommendations and sentiment based on the portfolio dynamics of less-informed investors (i.e who neglect a free opportunity to get more information and professional advice).

From this univariate analysis, we can draw the very preliminary (paradoxical?) conclusion that (voluntarily) well-informed investors are “noise traders”when it comes to measure sentiment and forecast returns. In a sense, it is a good point in favor of market efficiency. However, the fact that 1) approximately 50% of our sample belongs to the category of A-investors, who neglect free information and 2) $AMSI$ and RES help to forecast returns, leads to the reverse conclusion. Informational efficiency is for from being satisfied. This preliminary analysis shows that a multivariate analysis is useful to conclude whether sentiment really forecasts returns or whether it is only a combination of usual risk factors.

4.2 Multivariate analysis

Our conjecture is twofold. First, RES is the best predictor of future returns among the four sentiment measures ($SMSI$, $AMSI$, MSI and RES). Second, $SMSI$ is a worse

[16]There is also a significant difference between mid caps and large caps. However, to follow the standard methodology, we mainly analyze the long-short portfolio of the last column, long on small caps and short on large caps.

predictor than $AMSI$. To address these conjecture, we compare the performance of the four market sentiment indexes as predictors of future returns on a long-short portfolio based on size.

As mentioned above, the "sentiment seesaw"implies that the long-short portfolio return is high after low-sentiment periods and low after high-sentiment periods (Baker and Wurgler (2007)). When regressing the return of the long-short portfolio on sentiment indexes, we expect a negative sign for the coefficient of the lagged sentiment measures.

We replicate the methodology of Baker and Wurgler (2006) that contains two steps. In this approach, the dependent variable is $R_{Smallcaps,t} - R_{Largecaps,t}$, where $R_{Smallcaps,t}$ ($R_{Largecaps,t}$) is the return on a value-weighted portfolio built with the tercile of small (large) European stocks.

In the first step, we estimate the following regression equation:

$$R_{Smallcaps,t} - R_{Largecaps,t} = \alpha + \beta_s.Sentiment_{t-1} + \varepsilon_t \tag{3}$$

where $Sentiment_t$ is the sentiment index for month t and may be either MSI, $SMSI$, $AMSI$ or RES.

In the second step, we control for Fama-French-Carhart factors with the following regression model:

$$R_{Smallcaps,t} - R_{Largecaps,t} = c + \beta_s.Sentiment_{t-1} + \beta_{\mathbf{X}}\mathbf{X}_t + \varepsilon_t \tag{4}$$

The vector $\mathbf{X}$ of control variables includes the market factor (MKT) and the two Fama-French-Carhart factors, namely the book-to-market factor (HML) and the momentum factor (MOM). The size factor is not included in the equation because it is almost perfectly correlated with the dependent variable. The data for these factors come from the Eurofidai database.

Insert Table 5 here

Table 5 provides the results of the two regressions. Panel A (B) provides the regression coefficients of equation 3 (4) without (with) control for the Fama-French-Carhart factors. The expected negative sign for the sentiment coefficient (β_s) appears in the two models. The most significant coefficients are those of $AMSI$ and RES. The $SMSI$ coefficient is insignificant in both models. These findings indicate that sentiment measures built on the portfolio dynamics of A-investors are much better predictors of future returns, compared to measures based on the well-informed S-investors (even if they are more active in terms of trading volume). Consistent with the extant literature, we find that periods of high (low) sentiment are followed by low (high) returns on the long-short portfolio, even after controlling for the market, book-to-market, and momentum factors.

We also observe that the portfolio dynamics of A-investors better predicts future returns than the corresponding indicator built with S-investors. The results for $SMSI$ suggest that many trades executed by S-investors are not informative about their portfolio dynamics when characterized by the MSI. It is not surprising because trades completed by investors accessing to information and professional recommendations can be motivated by portfolio management concerns. Tables 1 and 2 show that S-investors hold more diversified portfolios, are more financially literate on average, and more wealthy than A-investors. This could suggest that a part of their trades does not change the number of different stocks they hold because they are motivated by portfolio adjustments. Such trades do not move the sentiment index.[17]

Finally, Table 5 shows that the adjusted R^2 is largely improved by the introduction of sentiment in the controlled version of the model, especially when we consider the variable RES. In that case, the adjusted R^2 reaches 21%.

5 Robustness tests

In this section, we perform three types of tests. First, we take into account the possible autocorrelations of sentiment measures that could overestimate the predictive power of sentiment. Second, as we interpreted the difference between A-investors and S-investors observed in Table 5 in terms of appetite for information and differences in decision processes, we have to rule out some alternative explanations. In particular, we test whether the differences between A-investors and S-investors can come from differences in cultural background, in financial literacy or in wealth. Finally, we build matched samples of investors on the three criteria of spoken language, financial literacy and wealth and

[17] We do not say that sentiment is absent of these trades, but only that an other sentiment index like a buy-sell imbalance measure should be used to take into account the sentiment of S-investors.

replicate the main analysis to check whether RES remains a predictor of future returns.

5.1 Autocorrelation of sentiment measures

As mentioned in Roger (2014), the regressions in Table 5 can produce biased estimators of β_s when *Sentiment* is an autoregressive process. The predictive power of *Sentiment* could be therefore overstated. We use the method of Stambaugh (1999) and Amihud and Hurvich (2004) to reduce the bias of the estimator.

Let the regression of $Sentiment_t$ on $Sentiment_{t-1}$ be written as:

$$Sentiment_t = \theta + \rho Sentiment_{t-1} + \nu_t \tag{5}$$

1) The estimate $\widehat{\rho}$ is corrected as follows

$$\widehat{\rho}^c = \widehat{\rho} + \frac{1+3\widehat{\rho}}{n} + \frac{3(1+\widehat{\rho})}{n^2} \tag{6}$$

where $n = 51$ when the regression covers the entire sample period.

2) The residuals of regression are estimated using $\widehat{\rho}^c$ and denoted by $\nu^c = (\nu_t^c, t = 1, ..n)$. The vector v^c is introduced in regression (3) which becomes

$$R_{Smallcaps,t} - R_{Largecaps,t} = \alpha + \phi \nu_t^c + \beta_s Sentiment_{t-1} + \varepsilon_t \tag{7}$$

In the controlled case, the equation writes

$$R_{Smallcaps,t} - R_{Largecaps,t} = c + \beta_s.Sentiment_{t-1} + \beta_{\mathbf{X}} \mathbf{X}_t + \phi \nu_t^c + \varepsilon_t \tag{8}$$

Finally, the corrected standard error of β_s is

$$\widehat{SE}^c(\beta_s) = \sqrt{\widehat{\phi}^2 Var(\widehat{\rho}^c) + \widehat{SE}^2(\beta_s)} \tag{9}$$

where $\widehat{SE}^c(\beta_s)$ is used to calculate the significance of the estimator of β_s in Table 6.

A comparison of Tables 5 and 6 leads to two main comments. First, the significant coefficients are the same in both tables and the significance levels are comparable. In particular, the coefficients of RES are virtually unchanged. This is not surprising because

RES is already the residual of the regression of $AMSI$ on $SMSI$. As a consequence, the autocorrelation of this sentiment indicator is much lower than that of the other sentiment indicators. The level of autocorrelation vary between 0.281 for RES to 0.507 for $SMSI$. The main difference between the two tables lies in the adjusted R^2. In most cases, the adjusted R^2 is higher in Table 6 because one more explanatory variable (v_t) appears in the model. The only exception concerns the sentiment indicator RES in the controlled case, for which the adjusted R^2 decreases. This observation is consistent with our preceding remark concerning the low autocorrelation of this variable.

Insert Table 6 here

5.2 Language and cultural background

The two main languages spoken in Belgium are French and Dutch. Our sample is well balanced as shown in Table 7. 20,036 investors are French-speakers and 25,049 are Dutch speakers. In the Belgian population, there are twice as more people in the Flemish region (populated by Dutch speakers) than in the Walloon region (populated by French speakers).[18] There are a number of cultural and economic differences between these two communities. Such differences could imply a different appetite for information and/or a different attitude with respect to professional advice, etc. For example, a report of the Council of Europe in 2001 states (of Europe, 2001): “Taking the form of a triangle tilted from north-west to south-east, Belgium is traversed, on an east-west line running almost through its centre, by one of Europes oldest “cultural frontiers”. This corresponds roughly to the line at which Julius Caesars armies stopped in their conquest of Gaul in the 1st century BC. Latin exercised a decisive influence south of this line, but remained secondary north of it.”

Insert Table 7 here

In this subsection, we test whether the difference between $AMSI$ and $SMSI$ could be driven by a disequilibrium between French and Dutch speakers. Our test consists in dividing our sample in 4 sub-categories denoted A_FR, S_FR, A_NL, S_NL respectively.

[18] see 'Regional Accounts' on the website of the National Bank of Belgium, http://stat.nbb.be

The suffix FR stands for French and NL for Dutch.[19] A and S keep the same meaning as before.

We recalculate the sentiment indexes for the four subsamples and the associated variables RES_FR and RES_NL. The results are provided in the top 6 rows of Table 8. The left (right) part of the table provides the uncontrolled (controlled) regression results. For the two subsamples (French speakers and Dutch speakers), the variables RES are highly significant in both versions of the model (uncontrolled and controlled). Despite the different cultural and economic background, we observe a large difference between A-indexes and S-indexes. The S-index is never significant while the A and RES coefficients are always significant. In particular, the $t-$statistics of the RES coefficients vary between -2.197 and -4.067, showing that this variable is highly significant in all sub-samples. Nevertheless, we observe a difference between French speakers and Dutch speakers. For French speakers, the coefficients of A_FR are more significant than the RES_FR coefficients. The adjusted R^2 are also higher with the A_FR variable than with the RES_FR variable. For example, in the controlled case, the adjusted R^2 with A_FR is equal to 17.1% but it is only 13.1% with the RES_FR variable. However, in both cases, the adjusted R^2 is well larger than when sentiment is not included. With the subsample of Dutch speakers, the significance of RES_NL is much stronger than that of A_NL. In the controlled case, the adjusted R^2 with A_NL is equal to 13.5% but it goes up to 20.8% with the RES_NL variable. Beyond these minor differences, it appears that sentiment is more present in the portfolio dynamics of A-investors, as expected.

Insert Table 8 here

5.3 Financial literacy

In this subsection, we address financial literacy. Table 3 show that we have more A-investors than S-investors in the two levels of low financial literacy (henceforth LFL), the reverse being true in the other levels of high financial literacy (henceforth HFL). To keep only two subsamples with respect to literacy, we aggregate levels 0 and 1 to define the LFL subsample, and 2 and 3 to define the HFL subsample. The figures are available

[19]The Flemish language is close to the Dutch language and the Flemish part of belgium is essentially in the north of the country, closer to Netherlands than to France. See for example http://ies.berkeley.edu/enews/articles/flemishlanguage.html

in Table 7.

We replicate the analysis of subsection 5.2 for the four variables S_LFL, A_LFL, S_HFL, A_HFL and the two variables RES_LFL and RES_HFL. The results are reported in the middle of Table 8. For the subsample of low literate investors, we get the same result as before. The sentiment measure RES_LFL is a very good predictor of future returns with t-statistics respectively equal to -3.05 (-3.697) in the uncontrolled (controlled) case. The coefficients of the measure based on A-investors are also significant while the coefficients of S-investors are not significant with t-statistics lower than 1 in absolute value. The findings are different for investors who report a high financial literacy. No significant difference appears between the two subsamples of A and S investors. One explanation of this result could be seen in Table 3. More than 10% of investors (either A- or S-investors) self-report the highest level of financial literacy which corresponds to investors “who manage any aspect of financial markets ”. Most academic readers specialized in finance would not choose this level because they know that it is impossible to reach such a level of competence in globalized and complicated markets. Hence, choosing not to fill in the S test for these investors could also mean that they are already very well informed and benefit from professional advisors elsewhere. It is then not so surprising that no significant difference emerges between the highly literate A-investors and S-investors.

5.4 Portfolio value

The portfolio dynamics, and in particular its diversification degree, is influenced by the portfolio value in a mechanical way. Ceteris paribus, the number of stocks in a portfolio is lower for an investor who has only a few hundred or thousand euros to invest, compared to an investor whose portfolio is worth one or two hundred thousands euros. Table 1 shows that the portfolio value of 25% of A-investors (S-investors) is worth less than €997 (€1,696). This could suggest that the difference between the sentiment index of A-investors and S-investors can be significant for large portfolio values (above the median for example) but not for small portfolio values (under the median). Portfolios worth a few hundred euros are too constrained to generate a significant difference between A-investors and S-investors. In particular, for the most constrained investors, the purchase of a stock is often financed by the sale of another stock, keeping unchanged the number of different stocks in the portfolio.

We again replicate the analysis of subsection 5.2 to address the impact of portfolio value. The results are presented in Table 8. For the subsample of large portfolios (LPV), the coefficients of RES_LPV is still significant while the coefficients of A_LPV is no more significant. As expected, the results for the subsamples of low portfolio values (SPV) are mixed.

5.5 A-investors matched with S-investors

We finally use propensity score matching (Rosenbaum and Rubin (1983)) to simultaneously control for language, financial literacy, and portfolio value. Our purpose is to select two groups of "comparable" A-investors and S-investors, i.e. investors who will mainly differ for their appetite for information and professional recommendation s.

For this purpose, we compute the propensity scores using a logit model wherein the dependent variable, Y_i, is a binary variable that equals 1 if the investor i filled in the S-test and 0 otherwise. The probability of being a S-investor is conditioned on a set of regressors, X, and is given by $Prob[Y = 1|X] = \wedge(x\prime b)$, where $\wedge(.)$ is the logistic cumulative distribution function. The set of regressors is made of an intercept, one dummy for the language, N-1 dummies (that is 3) for the level of self-reported financial literacy, and the log value of one plus the investor's monthly average portfolio value. Our logit model is then the following:

$$Y_i = \alpha + \beta_1 NL_i + \beta_2 FL1_i + \beta_3 FL2_i + \beta_4 FL3_i + \beta_5 LOG(1 + MPV_i) \quad (10)$$

where NL_i is equal to one when the investor i is Dutch-speaking, $FL1_i$ is set to one when the investor i select the level 1 of financial literacy, $FL2_i$ is set to one when the investor i select the level 2 of financial literacy, $FL3_i$ is set to one when the investor i select the level 3 of financial literacy, and MPV_i refers to the monthly average portfolio value computed for the investor i.

Table 9 reports the results of the logit model. All the parameter estimates are statistically significant, expect the dummy variable for the highest level of financial literacy. When looking at the odds ratios, we observe a positive relationship between the probability of being a S-investor and all the regressors (except the intercept). The investors who self-report a higher literacy (level 1 or 2) or the investors who hold larger portfolios are more likely to display a higher appetite for financial information. This relationship is also present for Dutch-speaking investors, even if somewhat weaker.

Insert Table 9 here

Based on the propensity scores estimated by our logit model, we then match S-investors with A-investors using the caliper matching method with replacement. This approach is similar to the nearest available neighbor matching method, with an additional restriction to avoid bad matches. Each treated unit (S-investor in our case) is selected to find its closest control match (A-investor in our case) based on the propensity scores but the control's propensity score is required to be within a certain radius (named caliper).[20] This restriction implies that it is possible that some S-investors cannot be matched to a real "comparable"A-investor. We end up with a sub-sample of 7,929 S-investors and a corresponding sub-sample of 7,929 matched A-investors.[21]

Table 10 provides a comparison of both sub-samples for the control variables under scrutiny. Matched A-investors and S-investors do not differ anymore on portfolio value, spoken language and financial literacy. In addition to this univariate approach, we run the logit model on our matched sub-samples and the results are no more significant, except for the highest level of financial literacy at 10% level.[22]

Insert Table 10 here

We recalculate the sentiment indexes on the matched subsamples and duplicate the methodology used before. Table 11 reports the results. Panels A and B (C and D) refer to the regressions without (with) adjustment for autocorrelations. As the results are very close, we focus on Panels C and D. Moreover, we make comparisons with Table 6 that is devoted to the initial subsamples.

First, the coefficients of $AMSI$ and RES remain always significant at the 5% level on matched subsamples, even if the matched A-investors are comparable to the S-investors in terms of wealth, financial literacy and language. In particular, the matched sample of A-investors is more financially literate than the general A-sample as we can see when

[20] We set the caliper at 10^{-5}.

[21] Since we allow replacement, we have in fact 6,538 matched A-investors, some of them being matched to several S-investors.

[22] The detailed results are available upon request.

comparing Table 3 and Table 10. The significance of the coefficient of $AMSI$ is stronger in the matched subsample than in the initial sample and the reverse is true for the coefficient of RES. Concerning the adjusted R^2, we observe a decrease in the matched subsamples for $AMSI$ and RES and an increase for $SMSI$. This evolution means that the matching process neutralizes the common characteristics of the two subsamples of investors. RES is then a clean indicator taking into account the differences linked to the fact that some investors decided to fill in the two tests while the others preferred to neglect information and recommendations.

Insert Table 11 here

6 Conclusion

Thanks to a proprietary database, we have the opportunity to distinguish two categories of retail investors on the basis of their appetite for information and professional recommendations. A-investors, who fill in only an appropriateness test, neglect free information and professional recommendations. On the contrary, S-investors who also fill in a suitability test, get a free access (through the web platform) to an investment advice tool on stocks (which delivers more detailed information on stocks and professional recommendations). Our paper shows that the sentiment revealed by the portfolio dynamics of A-investors is a better predictor of returns on a long-short portfolio based on size. This result means that small (large) stocks are overvalued (undervalued) when sentiment is high. A sentiment index taking into account the peculiarities of A-investors is then even better to forecast future returns.

Our findings are robust to a number of variations and controls. In particular, it remains on subsamples of Dutch-speaking or French-speaking investors, despite the cultural and economic differences between of these two communities in Belgium. The result strengthens when we restrict the analysis to investors with the two lowest levels of financial literacy. These investors represent 56% of A-investors and 50% of S-investors. The significance of $AMSI$ and RES coefficients is still present for the subsample of investors in the upper half of portfolio values. However, among the less wealthy investors, only the coefficient RES remains significant. To simultaneously control for the three important variables that are 1) the cultural and economic backgrounds proxied by the spoken language, 2) the level of financial literacy and 3) the portfolio value, we use a matching procedure to get "comparable" A-investors and S-investors. Our final regression analysis shows that the coefficient of RES remains significant at the 5% level in all the tests.

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7 Appendix

7.1 Steady-state equilibrium of diversification levels

If N is a homogeneous Markov chain it is possible to find a steady-state equilibrium that is a vector $\pi' = (\pi_1, ..., \pi_K)$ such that π_k is the proportion of investors holding k stocks in the long run. For the vector π to exist, the following two conditions have to be satisfied.

Denote $Q^{(n)}$ the n-period transition matrix[23].

1. The Markov chain is irreducible. It is the case if for each pair (k, m) there exists n such that $Q^{(n)}(k, m) > 0$. It is generally said that k and m communicate.

2. The Markov chain is aperiodic. Denote $\mathcal{R}(k) = \{n \in \mathbb{N}^* \text{ such that } Q_t^n(k, k) > 0\}$ the set of return times of state k. The period of k, denoted by $p(k)$, is the greatest common divisor of the numbers in $\mathcal{R}(k)$. The chain is said aperiodic if $p(k) = 1$.

Conditions (1) and (2) are satisfied in our case because individual investors can buy new stocks or they can sell the stocks they hold without regulatory constraints.

Q_t being assumed identical for all investors, the elements of Q_t are estimated by:

$$Q_t\left(k, m\right) = \frac{\sum_{i=1}^{I} \mathbf{1}_{\left\{N_{t+1}^i = m\right\} \cap \left\{N_t^i = k\right\}}}{\sum_{i=1}^{I} \mathbf{1}_{\left\{N_t^i = k\right\}}} \tag{11}$$

where $\mathbf{1}_A$ is the indicator of the event A, valued 1 if A is true and 0 otherwise.

[23] The specific properties of homogenous Markov chains allow to evaluate the n-period transition matrix by means of the Chapman-Kolmogorov equations. The n-period transition probability matrix satisfies $Q^{(n)} = Q^n$.

Table 1
Descriptive statistics for investors' trading activity. The table reports the cross-sectional mean, median, lower and upper quartiles computed over the sample period respectively for trade-based variables, stock portfolio-based variables, and stock portfolio performance variables. '# trades on stocks' is the number of trades executed on stocks. '# trades on bonds' is the number of trades executed on bonds. '# trades on funds' is the number of trades executed on investment fund shares. '# trades on options' is the number of trades executed on options and warrants. '# trading months' is computed as the number of months between the first trade and the last trade on stocks. 'trade duration' is computed as the median number of days between two trades on stocks. '# stocks in portfolio' is the monthly average number of stocks in portfolio. 'portfolio value' is the monthly average portfolio value in euros. 'value by position' is the monthly portfolio value divided by the monthly number of stocks held in portfolio. 'turnover' is the monthly traded volume divided by the end-of-month portfolio value. 'monthly gross return' is the monthly average return, which captures the profitability of both trades and end-of-month portfolio market values. 'monthly net return' is the monthly average gross return, net of explicit transaction costs. Due to the presence of some outliers, we winsorize the cross-sectional mean returns with both a 99^{th} percentile and a 1^{th} percentile cutoff. 'A-investors' only filled in the A-test while 'S-investors' filled in both the A-test and the S-test. *, **, *** indicate that means or medians statistically differ at the level of respectively 10%, 5%, or 1%.

	A-investors				S-investors			
Panel A: Trade-based variables	Mean	Q3	Median	Q1	Mean	Q3	Median	Q1
# trades on stocks	43.73***	34	10***	3	60.38	56	20	7
# trades on bonds	0.08***	0	0	0	0.15	0	0	0
# trades on funds	2.67***	0	0	0	10.10	1	0	0
# trades on options	14.28**	0	0	0	16.57	1	0	0
# trading months	22.03***	38	20***	4	28.02	44	30	12
trade duration (#days)	53.35***	35	8.5***	2	38.37	24.5	7	2
Panel B: Stock portfolio-based variables	Mean	Q3	Median	Q1	Mean	Q3	Median	Q1
# stocks in portfolio	3.77***	4.33	1.84***	0.69	6.05	7.71	3	1.06
portfolio value (€)	36,956***	17,323	4,523***	997	48,477	28,491	7,539	1,696
value by position (€)	6,898	4,032	1,575***	534	6,084	4,049	1,727	652
turnover	4.11*	0.21	0.07***	0.03	1.81	0.23	0.09	0.04
Panel C: Stock portfolio performance variables	Mean	Q3	Median	Q1	Mean	Q3	Median	Q1
monthly gross return (%)	0.90	0.93	0.04	-0.67	0.72	0.85	0.03	-0.60
monthly net return (%)	0.57	0.78	-0.03**	-0.81	0.42	0.67	-0.06	-0.75

Table 2
Demographic characteristics of the investors. For each investor, the age is computed as the difference between 2012 and the year of birth. '% University degree' refers to the proportion of investors who report they hold an university degree or an equivalent. 'A-investors' only filled in the A-test while 'S-investors' filled in both the A-test and the S-test.

	A-investors	S-investors
Median age	47	48
% Females	18	10
% French-speaking	45	44
% Dutch-speaking	55	56
% University degree	67	73

Table 3
Financial literacy of the investors. This table reports the answer to one specific question of the A-test where investors have to self-assess their knowledge of financial markets on a scale of 4 levels. The level 0 is associated with a basic knowledge. The level 1 corresponds to 'a sufficient experience to understand well the importance of a good diversification of risks'. The level 2 states that the investor 'understands the functioning of the financial markets and knows that the fluctuations can be important and that the various sectors and categories of products have different characteristics relating to their revenue, growth and risk profile'. The level 3 refers to an experienced investor 'who manages any aspect of the financial markets'. 'A-investors' only filled in the A-test while 'S-investors' filled in both the A-test and the S-test.

Knowledge of financial markets	0	1	2	3
A-investors	28%	28%	32%	12%
S-investors	22%	28%	40%	11%

Table 4
Correlations between sentiment measures, factors and portfolios over the period January 2008 to March 2012. Panel A provides contemporaneous correlations and Panel B lagged correlations. The market sentiment indices are $SMSI$ ($AMSI$), based on the portfolio diversification dynamics of S-investors (A-investors), and MSI calculated with the complete sample of investors. RES denotes the residual of the regression of $AMSI$ on $SMSI$. The risk factors are the four Fama-French-Carhart factors: the market return MKT, the size factor SMB, the value factor HML, and the momentum factor MOM. These four factors come from the Eurofidai database. They are calculated as the corresponding factors on the U.S market. The three portfolios $Lcaps, Mcaps$ and $Scaps$ are also provided by Eurofidai and represent the returns of portfolios based on size terciles ($Lcaps$ for large caps, $Mcaps$ for midcaps and $Scaps$ for small caps). The last column "Small-Big" is the difference between the two portfolio returns $Scaps - Lcaps$
.

	MKT	SMB	HML	MOM	Lcaps	Mcaps	Scaps	Small-Big
	Panel A: Contemporaneous correlations-January 2008-March 2012							
SMSI	-0.354**	0.096	-0.107	0.051	-0.331**	-0.254*	-0.241	0.150
AMSI	-0.579***	0.188	-0.350**	0.260**	-0.564***	-0.465***	-0.437***	0.200
MSI	-0.475***	0.142	-0.231	0.150	-0.455***	-0.366**	-0.345**	0.176
RES	-0.633***	0.230	-0.526***	0.431***	-0.634***	-0.549***	-0.513***	0.182
	Panel B: Lagged correlations-January 2008-March 2012							
SMSI	-0.063	-0.162	0.166	-0.099	-0.030	-0.053	-0.083	-0.107
AMSI	-0.160	-0.291**	-0.000	0.054	-0.128	-0.231*	-0.257**	-0.267**
MSI	-0.108	-0.230*	0.090	-0.033	-0.075	-0.138	-0.166	-0.188
RES	-0.222*	-0.338**	-0.222	0.234	-0.203	-0.370***	-0.379***	-0.367***

Table 5

Coefficients of sentiment when regressing the returns of a long-short portfolio based on size, on sentiment measures. Panel A gives the coefficient of sentiment in the simple regression: $R_{Smallcaps,t} - R_{Largecaps,t} = \alpha + \beta_s Sentiment_{t-1} + \varepsilon_t$. Panel B provides the same coefficient when controlling for Fama-French factors and the Carhart momentum factor. The regression equation is then : $R_{Smallcaps,t} - R_{Largecaps,t} = \alpha + \beta_s Sentiment_{t-1} + \beta_{\mathbf{X}} \mathbf{X}_t + \varepsilon_t$ where the matrix $\mathbf{X}$ includes the market factor and the three Fama-French-Carhart factors MKT, HML, MOM (SMB is not included because the long-short portfolio is based on this criterion). The sentiment measures are the four measures $SMSI$, $AMSI$, MSI and RES. $AMSI$ ($SMSI$) is calculated with the sample of A-investors (S-investors) who filled in the appropriateness test (the two tests, appropriateness and suitability). MSI is calculated with the complete sample. RES is the residual of the regression of $AMSI$ on $SMSI$. When sentiment is not considered in the controlled equation, the adjusted R^2 of the regression is 0.073.

	SMSI	**AMSI**	**MSI**	**RES**
	Panel A: Equation (3) without controls			
β_s	−0.060	−0.118**	−0.095	−0.310***
t-stat	−0.703	−2.320	−1.384	−3.241
p-val	0.485	0.024	0.172	0.002
$\overline{\mathbf{R}}^2$	−0.009	0.052	0.015	0.117
	Panel B: Equation (4) with controls			
β_s	−0.088	−0.137***	−0.120*	−0.336***
t-stat	−1.211	−2.807	−1.967	−3.398
p-val	0.232	0.007	0.055	0.001
$\overline{\mathbf{R}}^2$	0.077	0.152	0.110	0.213

Table 6
Coefficients of sentiment when regressing the returns of a long-short portfolio based on size, on sentiment measures, using the reducing-bias technique of Amihud and Hurvich (2004). Panel A gives the coefficient of sentiment in the simple regression: $R_{Smallcaps,t} - R_{Largecaps,t} = \alpha + \beta_s Sentiment_{t-1} + \phi v_t + \varepsilon_t$. Panel B provides the same coefficient when controlling for Fama-French factors and the Carhart momentum factor. The regression equation is then : $R_{Smallcaps,t} - R_{Largecaps,t} = \alpha + \beta_s Sentiment_{t-1} + \beta_{\mathbf{X}} \mathbf{X}_t + \phi v_t + \varepsilon_t$ where the matrix $\mathbf{X}$ includes the market factor and the three Fama-French-Carhart factors MKT, HML, MOM (SMB is not included because the long-short portfolio is based on this criterion). The sentiment measures are the four measures $SMSI$, $AMSI$, MSI and RES. $AMSI$ ($SMSI$) is calculated with the sample of A-investors (S-investors) who filled in the appropriateness test (the two tests, appropriateness and suitability). MSI is calculated with the complete sample. RES is the residual of the regression of $AMSI$ on $SMSI$. When sentiment is not considered in the controlled equation, the adjusted R^2 of the regression is 0.073.

	SMSI	**AMSI**	**MSI**	**RES**
	Panel A: Equation (3) without controls			
β_s	−0.049	−0.113*	−0.086	−0.307***
t-stat	−0.541	−1.977	−1.141	−3.030
p-val	0.590	0.054	0.259	0.004
$\overline{\mathbf{R}}^2$	0.040	0.122	0.088	0.134
	Panel B: Equation (4) with controls			
β_s	−0.077	−0.125**	−0.106	−0.329***
t-stat	−0.998	−2.460	−1.642	−3.173
p-val	0.324	0.018	0.108	0.003
$\overline{\mathbf{R}}^2$	0.086	0.165	0.130	0.196

Table 7
Sub-samples of investors for the robustness checks. We report in the table the number of investors for each sub-sample under scrutiny. For the financial literacy, we use the specific question of the A-test where investors have to self-assess their knowledge of financial markets on a scale of 4 levels. In the 'Low financial literacy' sub-sample, we consider the investors who choose the first two levels while the investors who select the other two levels are put in the 'High financial literacy' sub-sample. To discriminate investors on the portfolio market value, we first compute the cross-sectional median monthly portfolio value across all the investors. The investors whose monthly average portfolio value is smaller (larger) than the cross-sectional median monthly portfolio value are put in the 'Small portfolio value' ('Large portfolio value') sub-sample. A-investors only filled in the A-test while S-investors filled in both the A-test and the S-test.

	A-investors	S-investors
French-speaking	10,489	9,547
Dutch-speaking	12,858	12,191
Low financial literacy	13,131	10,836
High financial literacy	10,216	10,902
Small portfolio value	12,633	9,910
Large portfolio value	10,714	11,828

Table 8
Regression coefficients of sentiment measures on sub-samples
S, A denote sentiment measures built with, respectively S-investors and A-investors. RES denotes the residual of the regression of the A-based measure on the S-based measure. The suffixes FR and NL denote the main language spoken by the investors (FR for French or NL for Dutch). For example, A_FR is the sentiment measure built on the portfolio dynamics of the subset of A-investors who are French speakers. The suffixes LFL and HFL identify the self-reported financial literacy (low for LFL, high for HFL). LPV and SPV identify the subsamples based on portfolio value. LPV (SPV) means large (small) portfolio value

		NO	CONTROL			CONTROL		
Variable	Coefft	t-stat	p-value	R^2	Coefft	t-stat	p-value	R^2
S_FR	-0.091	-1.234	0.224	0.065	-0.106	-1.682	0.100	0.109
A_FR	-0.108**	-2.285	0.027	0.136	-0.116**	-2.664	0.011	0.171
RES_FR	-0.184**	-2.197	0.033	0.082	-0.188**	-2.215	0.032	0.131
S_NL	-0.006	-0.066	0.948	-0.010	-0.035	-0.464	0.645	0.047
A_NL	-0.101*	-1.743	0.088	0.077	-0.117**	-2.349	0.023	0.135
RES_NL	-0.274***	-3.164	0.003	0.111	-0.327***	-4.067	0.000	0.208
S_LFL	-0.029	-0.373	0.711	0.037	-0.055	-0.864	0.392	0.089
A_LFL	-0.106**	-2.312	0.025	0.171	-0.116***	-2.828	0.007	0.205
RES_LFL	-0.249***	-3.050	0.004	0.164	-0.268***	-3.697	0.001	0.235
S_HFL	-0.073	-0.771	0.444	0.001	-0.092	-1.078	0.287	0.056
A_HFL	-0.087	-1.189	0.240	0.020	-0.102	-1.631	0.110	0.085
RES_HFL	-0.122	-1.062	0.294	-0.012	-0.129	-1.300	0.200	0.066
S_LPV	-0.024	-0.166	0.868	0.019	-0.033	-0.267	0.790	0.063
A_LPV	-0.119	-1.638	0.108	0.058	-0.109*	-1.698	0.097	0.095
RES_LPV	-0.262**	-2.606	0.012	0.055	-0.242**	-2.665	0.011	0.107
S_SPV	-0.076	-0.937	0.354	0.044	-0.137*	-1.997	0.052	0.123
A_SPV	-0.123*	-1.890	0.065	0.136	-0.210***	-3.629	0.001	0.247
RES_SPV	-0.262	-1.442	0.156	0.040	-0.369*	-1.935	0.059	0.163

Table 9
This table reports the results for the logit model wherein the dependent variable, Y_i, is a binary variable that equals 1 if the investor i filled in the S-test and 0 otherwise. NL_i is equal to one when the investor i is Dutch-speaking, $FL1_i$ is set to one when the investor i select the level 1 of financial literacy, $FL2_i$ is set to one when the investor i select the level 2 of financial literacy, $FL3_i$ is set to one when the investor i select the level 3 of financial literacy, and MPV_i refers to the monthly average portfolio value computed for the investor i. *, **, *** indicate that parameter estimates are statistically significant at the level of respectively 10%, 5%, or 1%. The odds ratio for a given explanatory variable is the exponential of its estimated coefficient. When the independent variable is continuous, the odds ratio measures how the probability of success changes if the variable increases by one unit (from x to x+1). For a binary variable, the odds ratio assesses how the probability that the event will occur changes when the variable goes from zero to one. If the odds are greater (lower) than one, then the event is more (less) likely to happen.

Independent variables	Parameter estimates	Odds Ratios	95% Wald Confidence Limits	
Intercept	-1.0533***			
FL1	0.1909***	1.210	1.149	1.275
FL2	0.3710***	1.449	1.379	1.523
FL3	0.0121	1.012	0.945	1.084
NL	0.0366*	1.037	0.999	1.077
LOG(1+MPV)	0.0908***	1.095	1.085	1.105

Table 10
This table reports the results of mean comparisons for control variables between S-investors and matched A-investors. Investors' matching is based on the results of the logit model presented in Table 9, using a propensity score matching (with replacement) to simultaneously control for language, financial literacy, and portfolio value. NL_i is equal to one when the investor i is Dutch-speaking, $FL0_i$ is set to one when the investor i select the level 0 of financial literacy, $FL1_i$ is set to one when the investor i select the level 1 of financial literacy, $FL2_i$ is set to one when the investor i select the level 2 of financial literacy, $FL3_i$ is set to one when the investor i select the level 3 of financial literacy, and MPV_i refers to the monthly average portfolio value computed for the investor i. *, **, *** indicate that mean differences are statistically significant at the level of respectively 10%, 5%, or 1%. 'A-investors' only filled in the A-test while 'S-investors' filled in both the A-test and the S-test.

	Matched A-investors	S-investors
NL	0.5564	0.5614
FL0	0.2143	0.2073
FL1	0.3179	0.3293
FL2	0.3592*	0.3462
FL3	0.1086*	0.1172
MPV	28,879	27,287
LOG(1+MPV)	8.6847	8.7107

Table 11

Coefficients of sentiment when regressing the returns of a long-short portfolio based on size, on sentiment measures calculated over the period February 2008 to March 2012 on matched samples. Panels A and B provide the unadjusted results calculated as in table 5. Panels C and D provide results adjusted for autocorrelation of sentiment measures, as in table 6. Panel A (C) gives the coefficient of sentiment in the simple regression: $R_{Smallcaps,t} - R_{Largecaps,t} = \alpha + \beta_s Sentiment_{t-1} + (+\phi v_t) + \varepsilon_t$. Panel B (D) provides the same coefficient when controlling for Fama-French factors and the Carhart momentum factor. The regression equation is then : $R_{Smallcaps,t} - R_{Largecaps,t} = \alpha + \beta_s Sentiment_{t-1} + \beta_{\mathbf{X}} \mathbf{X}_t (+\phi v_t) + \varepsilon_t$ where the matrix $\mathbf{X}$ includes the market factor and the three Fama-French-Carhart factors (size is not included because the portfolio is based on this criterion). The sentiment measures are the measures $SMSI$, $AMSI$, and RES. $SMSI$ ($AMSI$) is calculated with the sample of S-investors who filled in the two tests (the appropriateness test). RES is the residual of the regression of $AMSI$ on $SMSI$. When sentiment is not considered in the controlled equation, the adjusted R^2 of the regression is 0.073.

	SMSI	**AMSI**	**RES**
	Panel A: Matched sample-Equation (3) without controls		
β_s	-0.007	-0.119**	-0.222***
t-stat	-0.083	-2.239	-2.879
p-val	0.933	0.030	0.005
$\overline{\mathbf{R}}^2$	-0.021	0.065	0.134
	Panel B: Matched sample-Equation (4) with controls		
β_s	-0.058	-0.124**	-0.207***
t-stat	-0.842	-2.563	-3.038
p-val	0.404	0.014	0.003
$\overline{\mathbf{R}}^2$	0.062	0.147	0.180
	Panel C: Matched sample-Equation (7) without controls		
β_s	0.002	-0.118**	-0.222***
t-stat	0.019	-2.179	-2.835
p-val	0.984	0.034	0.006
$\overline{\mathbf{R}}^2$	-0.007	0.084	0.119
	Panel D: Matched sample-Equation (8) with controls		
β_s	-0.044	-0.121**	-0.212***
t-stat	-0.593	-2.509	-3.196
p-val	0.556	0.016	0.003
$\overline{\mathbf{R}}^2$	0.053	0.132	0.163