Beyond the Disposition Effect:
Evidence from the 1999-2012 period

Anthony Bellofatto[a], Rudy De Winne[b] and Catherine D'Hondt[c]

Université catholique de Louvain, Louvain School of Management

Working Paper

This version: March 27, 2014

Abstract

This paper provides an in-depth analysis of how the disposition effect (DE) varies both across individual investors and over time. We bring evidence that financial sophistication, either directly observed or assessed through some MiFID tests items, helps investors reduce this behavioral bias. We also identify the use of stop-loss orders as an effective tool for investors to dampen their DE. Moreover, investors who asked for investment advice are associated with a significantly lower DE, which suggests that investment firms reduce their clients' exposure to this behavioral bias. We also report that some personal traits play a role in the exposure to the DE. In particular, retail investors who stated a large tendency to realize sharp losses or investors qualified as "aggressive" through the Suitability test display a significantly lower DE. All in all, our findings suggest that MiFID tests are really informative. As for the DE over time, we observe a significantly lower DE when markets are falling (especially during crisis periods such as the financial crisis of 2008) and the highest DE when markets are booming such as in the mid 2000's. Furthermore, we point out a financial stock-specific effect, even after controlling for investor's characteristics. Specifically, we observe that the DE variation over time is exacerbated when focusing on financial stocks, which suggests that stock characteristics are additional drivers of this behavioral bias.

JEL Classification: G01, G02, G11, G23, G28

Keywords : Disposition effect, retail investors, behavioral biases, MiFID

The authors are grateful to the Belgian online brokerage house for providing the data. Any errors are the responsibility of the authors. Contact address: Université catholique de Louvain - Louvain School of Management, Chaussée de Binche 151, 7000 Mons, Belgium. Email adresses: (a)anthony.bellofatto@uclouvain.be; (b)rudy.dewinne@uclouvain.be; (c)catherine.dhondt@uclouvain.be.

1 Introduction

For more than two decades, behavioral finance challenges the assumption of investor rationality and allows for explanations of financial phenomena that are still puzzles for traditional finance. In this growing body of research, the disposition effect (DE hereafter) is particulary well-established and documented. Labeled initially by Shefrin and Statman (1984), this behavioral bias refers to investors' reluctance to realize losses (keep "losers") as well as their propensity to realize gains (sell "winners").

In the literature, the DE has been first outlined at the aggregate level, i.e. for a given market or representative groups of investors (a.o. Odean (1998), Grinblatt and Keloharju (2001), Barber et al. (2007)). The presence of this bias has then been addressed at the individual level, in order to account for heterogeneity across investors as well as the evolution of an individual's behavior over time (a.o. Feng and Seasholes (2005), Dhar and Zhu (2006), Boolell-Gunesh et al. (2012)). The main findings confirm the presence of the DE for the average investor and show that both investor's sophistication and trading experience tend to significantly reduce this bias.

The motivations for conducting research on the DE is twofold. First, it contributes to a better understanding of investors' behavior and to a larger extent of market functioning. In particular, the DE is suspected to impact on both price formation and trading activity. The tendency to hold on "losers" and to sell "winners" may create imbalance between supply and demand, thereby potentially altering price formation. For example, Grinblatt and Han (2005) and Frazzini (2006) suggest that the DE can generate underreaction to news and in turn momentum and return predictability as well as post-announcement price drift. Hur et al. (2010) also show that the momentum effect driven by the DE is stronger in markets dominated by individual investors. Concerning trading activity, several papers report that the DE may generate abnormal volume. By comparing "winners" to "losers", Lakonishok and Smidt (1986) show that the trading volume of "winners" is significantly higher. More recently, Statman et al. (2006) highlight that stock turnover is positively related to lagged returns and they relate this result to investors' overconfidence and DE.

The second motivation for addressing the DE arises because investors the most subject to this bias are also associated with the lower trading performances (Dhar and Zhu (2006)). As a consequence, better characterizing the DE may deliver relevant insights for regulatory purposes, especially for retail investors' protection. It may also be useful for investment firms who strive to provide their clients with suitable advice or warn them before investing in an inappropriate instrument, as explicitly requested since the implementation of the European Markets in Financial Instruments Directive (MiFID).

In this paper, we report an in-depth analysis of the DE both across individual investors and over time, and we contribute to the literature on several aspects.

First, we provide additional results about the relationship between investor's sophistication and the DE level. For this purpose, we use a unique database from an important Belgian online brokerage house to investigate the behavior of more than 50 000 retail investors during the 1999-2012 period. In particular, this database includes usual information relative to investors' orders and trades but also their answers to the MiFID questionnaires.[1] Indeed, since November 2007, investment firms operating in the EU are forced to submit tests to their clients to determine their level of knowledge, their experience in complex instruments and their investment profile, in order to offer them suitable services accordingly. Specifically, MiFID requires a Suitability test, where the firm asks the investor some questions to reach an understanding of the types of investments that will be suitable for him, and an Appropriateness test in the framework of execution and submission of orders, which aims at assessing the experience in complex financial instruments to protect the investor who may not understand or be aware of the implications and level of risk involved in a 'complex' transaction (i.e. involving 'complex' financial instruments[2]).

The data at hand allow us to address in great detail the link between the investor's profile and his DE. Indirect measures of sophistication are often used in the literature. For example, Dhar and Zhu (2006) define both professional occupation and available income as proxies of retail investors' sophistication. To our knowledge, only two studies use direct measures. Feng and Seasholes (2005) refer to the number of stocks and the number of trading rights as proxies of sophistication. More recently, Boolell-Gunesh et al. (2012) provide a comprehensive set of direct sophistication measures derived from retail investors' trading behavior. For example, they consider investors to be sophisticated if they trade foreign assets or derivatives.

Building on Boolell-Gunesh et al. (2012), we extend the range of direct sophistication proxies and examine new variables that are significantly related to the DE level such as the type of orders. To the best of our knowledge, only Linnainmaa (2010) investigates the link

[1] The data are anonymized.

[2] Examples of 'complex' financial instruments are: options, futures, swaps, financial contracts for differences, convertible bonds, warrants and other derivatives.

between the DE and the type of orders but for other purposes. Basically, he shows that the use of limit orders generates a trading pattern that is mechanically equivalent to the DE. In this paper, we check whether the use of stop-loss orders helps investors to dampen the DE.

In addition, using the answers to the MiFID tests, we adopt a complementary approach where sophistication is measured by 'assessment' of retail investors' financial literacy and where investors's profile and personal traits are related to the DE. This approach constitutes a major contribution to the literature since no study has so far investigated MiFID questionnaires, which contain unique and relevant information for research in behavioral finance.

Another contribution is related to our sample period that is large and recent (1999-2012), which allows us to take into account the temporal dimension of the DE and the impact of the recent financial crises. For this purpose, we investigate how both time and financial market conditions influence individual investors' behavior and the DE.

Finally, we also examine the relationship between the type of stock traded and the DE. To the best of our knowledge, only Ranguelova (2001) reports a stock specific-effect on the DE. More precisely, she shows that there is a monotonic negative relationship between the DE of an investor and the market capitalization of the stocks he trades. Based on this paper, we focus on the type of stock traded (financial or not) and investigate how it impacts the DE of retail investors.

Our main findings may be summarized as follows.

Regarding the DE across investors, we find out that financial sophistication, either directly observed or assessed through some MiFID tests items, helps investors reduce this behavioral bias. First, investors who are aware of diversification benefits and involved either in a more risky trading strategy (day trading) or in a more sophisticated financial investment choice (investment fund shares trading) exhibit a significantly lower DE. Second, we identify the use of stop-loss orders as an effective tool for investors to dampen their DE. We also find that a perception of better financial market knowledge and a higher education degree are both negatively related to the DE. Moreover, investors who asked for investment advice are associated with a significantly lower DE, which suggests that investment firms reduce their clients' exposure to this behavioral bias. We also bring evidence that some personal traits play a role in the exposure to the DE. In particular, retail investors who stated a large tendency to realize sharp losses or investors qualified as "aggressive" through the Suitability test display a significantly lower DE.

All in all, the findings based on the MiFID tests are consistent with the results obtained for direct proxies of sophistication, suggesting these tests are really informative to characterize investors and their exposure to the DE. Given their relevance, they may be useful for investment firms as well as for regulators in their concern to characterize investors and provide them with suitable services in a protection perspective.

As for the DE over time, our results bring evidence that crisis periods (such as the internet bubble and the 2008 financial crisis) play a significant role in the variation of the aggregate investor's DE. By contrast to "normal" market conditions, the aggregate investor seems to display a significantly lower DE when markets are falling while he exhibits the highest DE when markets are booming such as in the mid 2000's. We find that in downturn periods, investors are less prone to realize their gains.

Finally, we point out a financial stock-specific effect, even after controlling for investor's characteristics. Basically, for a given investor, the DE on financial stocks is significantly different from the DE on other types of stocks. More precisely, we observe that the DE variation over time (decrease during bearish periods and increase during bullish periods) is exacerbated when focusing on financial stocks. These findings suggest that stock characteristics are additional drivers of this behavioral bias.

The remainder of this paper is structured as follows. Section 2 provides a short review of the extant literature on the DE. Section 3 describes our data and sample as well as the MiFID tests. The methodology is presented in Section 4. We report our empirical work and its results in Section 5. Section 6 concludes.

2 Literature

The DE is related to two major theories underlying behavioral finance: the Prospect Theory of Kahneman and Tversky (1979) and the Mental Accounting of Thaler (1985).

By contrast to the expected utility maximization assumed in traditional finance, the Prospect Theory states that individuals take their decisions on the basis of gains and losses evaluation compared to a reference point. Accordingly, individuals' decision making in presence of incertitude follows a valuation function v(x) that depends on x, the deviation from the reference point as illustrated on figure 1.[3] In this approach, each decision is evaluated based on gains and

[3]This figure is replicated from Oehler et al. (2003).

losses calculated from the reference point rather than on the final result. The value function is therefore positive in the gains domain and negative for the losses. In addition, since the value of additional gains or losses is assumed to decrease as we move from the reference point, the value function is concave in the domain of gains and convex in the domain of losses. Hence the Prospect Theory suggests that individuals are "risk-averse" in the domain of gains and "risk-seeker" in the domain of losses, following the S-curve in figure 1.

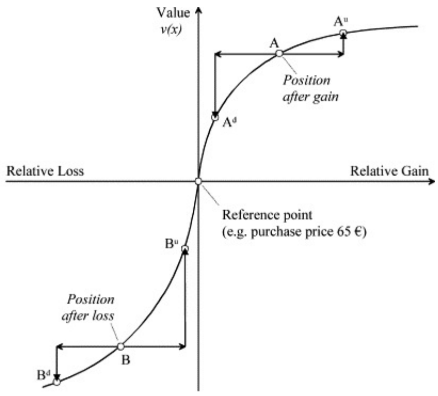

Figure 1: Value function

Thaler (1985) defines the Mental Accounting as "*the set of cognitive operations used by individuals and households to organize, evaluate, and keep track of financial activities*". This theory assumes that individuals treat their income sources differently given their origin, nature and usage. According to this approach, individuals divide their wealth into different mental accounts and value separately each decision they face for each mental account. They apply then decision making rules without considering potential interactions between the decisions and the consequences at a global level. Expanding the partition, the Mental Accounting suggests that an investor may open a new mental account each time he takes a position in a specific security. In that perspective, investors consider each security separately from the portfolio, which could lead to mental account specific decision making. An investor may therefore be unwilling to realize a loss for a given position as this loss will be recorded in that mental account, even though it harms the global portfolio performance. This behavior is also consistent with the idea that investors prefer self-esteem (pride from realizing profits) to regret (due to erroneous investment decisions), as outlined by Subrahmanyam (2007).

Shefrin and Statman (1984) are the first to bring empirical evidence for the DE in financial markets. Using transactions at a brokerage house, they find that retail investors realize gains more rapidly than losses and label this tendency as DE. Odean (1998) shows that this behavioral bias is neither motivated by a desire to rebalance portfolios nor by subsequent portfolio performances (driven by irrational belief in the mean-reversion). The authors find similar conclusions for transaction costs. Since these reference papers, the DE is well-established and has been documented in a large panel of empirical studies.[4]

Characterizing investors subject to the DE is an important question in the literature. Grinblatt and Keloharju (2001) study the DE for five investor types: non-financial corporation, financial and insurance institutions, governmental organizations, non-profit institutions and households. Their results reveal that all are subject to the DE, even if its level varies across categories. Building on this paper, several studies address heterogeneity in behavior across investors, with a specific focus on the link between the DE and financial sophistication. Using indirect measures of sophistication (such as professional occupation and income in Dhar and Zhu (2006)) or direct proxies (such as number of stocks and number of trading rights in Feng and Seasholes (2005)), the findings show that the financial sophistication of investors dampens the DE. Some sophisticated investors display even the Reverse DE (Talpsepp (2011)).

Recently, Boolell-Gunesh et al. (2012) extend the range of financial sophistication proxies and provide a comprehensive set of direct measures derived from the trading behavior of retail investors. Specifically, they consider investors to be sophisticated if they trade foreign assets, derivatives, bonds, and if they hold multiple accounts to place orders on. They hypothesize that retail investors trading "non-traditional" instruments are sophisticated because they are more aware of diversification benefits. Furthermore, they assume that the holding of both a traditional account and a tax-free account is a feature of higher sophistication because the investor takes advantage of the flexibility offered by the first account and simultaneously of the potential tax cut attached to the second one. Their results show that investors associated with higher financial sophistication exhibit a significantly lower DE. In addition, the authors find that individual investor's DE decreases over time and that sophistication plays a role in that decrease.

The relationship between the DE and market conditions is another relevant question addressed in recent work. Focusing on the 1999-2002 period on the Portuguese Stock Exchange, Leal et al. (2006) document that, although the DE is clearly exhibited at the aggregate level in both bull and bear periods, this bias is much more pronounced during the bull market peri-

[4] Most of the papers report empirical investigations. One exception is Weber and Camerer (1998) who conduct an experimental study on German students.

ods. On the contrary, Cheng et al. (2013) demonstrate that a bear market displays a stronger disposition effect on the Taiwan Future Exchange during the 2003-2007 period.

To the best of our knowledge, the link between the type of stock traded and the DE is only investigated in Ranguelova (2001). Her results indicate that there is a monotonic negative relationship between the DE of an investor and the stock market capitalization.

3 Data and Sample Characteristics

3.1 Data

The data at hand are provided by an online brokerage house and cover the 1999-2012 period. They refer to 51 098 retail investors, who traded together on 9945 different stocks. They are made of two files. The first file contains anonymous information about the investors, that we classify into three categories. The first category includes demographics: date of birth, gender, profession, education level, language, and marital status. The second category encompasses the answers to the MiFID Appropriateness test. The third category contains the answers to the MiFID Suitability test for the 23 366 investors who asked for investment advice. The second file is made of detailed information about the investors' trading activity. That includes the stock ISIN code, order size, price, type, executed quantity, trade price, as well as a code for the market where the trade was completed.

In addition to those data, we have the daily HLOC prices over the 1999-2012 period for the 9945 stocks under scrutiny.

3.2 MiFID tests

MiFID came into force in 2007 across the EU member states. One of its objectives was to increase the level of protection for investment firms' clients. In addition to client categorization aiming at segregating retail investors from professional investors and eligible counterparts, MiFID requires investment firms to qualify their clients and the services requested through Suitability and Appropriateness tests. These two level of qualification depend on the type of services provided to the investor.

The Suitability test (S-test hereafter) has to be passed before providing investment advice or portfolio management. Assessment of suitability involves ensuring that the instruments and services offered meet the investor's objective, financial situation as well as his knowledge and experience in financial instruments. As mentioned earlier, our data contains the answers to the S-test only for the investors who asked for investment advice (23 366 in our sample, that is 46%).[5] Basically, implementing the S-test mainly results in categorizing investors into four investment profiles: Conservative, Neutral, Dynamic or Aggressive.

The Appropriateness test (A-test hereafter) has to be passed before providing execution and transmission of orders in complex financial instruments. 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 that provides us with data has implemented this test in 2007 for an exhaustive list of instruments, including shares traded on a non-European market or on a European non-regulated market. As a result, we have the answers to the A-test for all the retail investors in our sample.

3.3 Sample descriptive statistics

Tables 1 and 2 present descriptive statistics for our panel of direct measures of financial sophistication as well as control variables. Based on demographics, both gender and age are common control variables. Our direct measures of sophistication are all derived from trading behavior. Some are frequently used such as the number of different stocks traded, the number of different markets, and the number of trades. All of them are usually viewed as good proxies of diversification and to a larger extent of financial sophistication. In particular, for the number of different markets in which a retail investor trades, we may assume that a relatively low-sophisticated investor is home-biased and invests preferentially and only in his local markets. Building on Boolell-Gunesh et al. (2012), we also consider whether investors trade investment fund shares since trading this type of instrument requires a higher financial knowledge. In addition, we look at new proxies such as day trading and use of stop-loss orders. As for the number of daily roundtrips, we assume that the frequency at which some investors take regularly opposite position on the same stock during the same day may be associated to a more expert trading activity. Finally, stop-loss orders could help investors cut more rapidly their losses and thus reduce the DE, as suggested in Shefrin (2007).

[5] The online brokerage house doesn't offer management services to its clients. It only provides an investment advice tool on stocks.

From table 1, we know that the average investor is 48 years old in 2012, trades about 16 different stocks across 4 markets, executes on average about 3 daily roundtrip trades and submits less than one stop-loss order over the entire 13-year period. Our sample is somewhat homogenous in terms of both age and number of markets.

Table 2 shows that 86% of the investors are men and that about one quarter of them are day traders or trade investment fund shares.

Table 1: Descriptive statistics of direct measures of financial sophistication (1)

	Mean	Median
Age_2012	48	47
Number of stocks	16.65	8
Number of markets	4.45	4
Number of trades	61.01	20
Number of day_trades	3.03	0
Number of stop_loss orders	0.45	0

The table reports the cross-sectional mean and median for age and direct measures of sophistication. 'Age_2012' is computed in year 2012 using the available date of birth of each retail investor. 'Number of stocks' is the number of different stocks traded during the sample period. 'Number of markets' is the number of different markets in which a retail investor has submitted at least one order. 'Number of trades' is the number of trades executed over the entire period. 'Number of day_trades' refers to the number of daily roundtrips executed over the entire period. 'Number of stop_loss orders' refers to the number of stop-loss orders submitted over the entire period.

Table 2: Descriptive statistics of direct measures of financial sophistication (2)

	0	1
Gender	14%	86%
Day_trader	74%	26%
Funds_trader	75.34%	24.66%

The table reports statistics for gender and direct measures of sophistication built on binary variables. 'Gender' is equal to 1 for men. 'Day_trader' is equal to 1 when the investor made at least one daily roundtrip. 'Funds_trader' is set to 1 when the investor made at least one trade on investment fund shares.

Information from the A-test is available in table 3, where the distribution of the answers to some items is provided. We will use these items as 'assessed' measures of financial sophistication. For both knowledge of financial markets and number of orders, we have a real heterogeneity among investors. Unsurprisingly, answers to both items are correlated. Only 12% of the investors consider themselves as really experienced investors. As for the education level, more than 70% of the investors have a university or equivalent degree.

Table 3: A-test

	0	1	2	3
Knowledge of financial markets	21.40%	29.42%	37.01%	12.17%
Number of orders placed per year	23.03%	38.60%	25.63%	12.74%
Highest education degree	5.64%	21.11%	73.25%	-

The table reports the distribution of the answers to some items of the A-test. For each item, the assessment grid is increasing. In the case of 'Knowledge of financial markets', the level 0 is associated with a basic knowledge while the level 3 refers to an experienced investor who manages any aspect of the financial markets. For the 'Number of orders placed per year', the item covers only the products listed for the A-test and the level 0 is associated with zero order while the level 3 refers to more than 36 orders. As for 'Highest education degree', the level 0 corresponds to no degree, the level 1 to secondary or high school degree, and the level 2 to university or equivalent degree. There is no third level for this item.

Table 4 exhibits the investment profile depending on the S-test score. More than 60% of the investors who passed the test are characterized as dynamic while less than 3% are conservative.

Table 4: S-test

	Conservative	Neutral	Dynamic	Aggressive
User_Profile	2.41%	22.52%	62.05%	13.02%

The table reports the investment profiles determined through the S-test. It gives the distribution of the 23 366 retail investors who passed the test among the four possible profiles.

4 Methodology

Using the traditional methodology introduced by Odean (1998), we compute the DE for each investor as the difference between his proportion to realize gains and his proportion to realize losses. Specifically, after an investor i trades a stock s, we compute each day either a Paper Gain/Loss or Realized Gain/Loss until he closes his position. A Realized Gain/Loss is computed by comparing the average purchase price of the stock and the selling price. To determine the Paper Gains and Losses, we adopt a conservative approach. Accordingly, a Paper Gain for a long (short) position is computed only if the daily lowest price of the stock is above (below) the average purchase price. A Paper Loss for a long (short) position is computed only if the daily highest price of the stock is below (above) the average purchase price. In the other cases, no Paper Gain/Loss is calculated.

The DE for the investor i on the stock s ($DE_{i,s}$) depends then on both his Proportion of Gains Realized ($PGR_{i,s}$) and his Proportion of Losses Realized ($PLR_{i,s}$), according to the following formulas:

$$PGR_{i,s} = \frac{NGR_{i,s}}{NGR_{i,s} + NPG_{i,s}}$$

$$PLR_{i,s} = \frac{NLR_{i,s}}{NLR_{i,s} + NPL_{i,s}}$$

$$DE_{i,s} = PGR_{i,s} - PLR_{i,s}$$

where NGR is the Number of Gains Realized, NPG the Number of Paper Gains, NLR is the Number of Losses Realized, and NPL the Number of Paper Losses.

For the purpose of our study, we exclude day trading activities of our sample (i.e. daily roundtrip on the same stock) to compute the DE. They are only used to characterize investors as day traders. In addition, when an investor trades the same day a same stock in the same direction, we compute a daily net trading.

To check the presence of the DE at an aggregate level, we first test the following common hypothesis:

$$H_0 = PGR \leq PLR$$

$$H_1 = PGR > PGR$$

In this perspective, we compute the t-statistics that follows a Student distribution with n-1 degrees of freedom:

$$t - stat = \frac{\overline{PGR} - \overline{PLR}}{\frac{S'_{ED}}{\sqrt{n-1}}}$$

To investigate how the DE varies both across individual investors and over time, we then formulate five hypotheses to be empirically tested with different regression models.

4.1 Hypothesis 1: Financial literacy measured by direct proxies has an impact on the DE

In order to test this hypothesis, we estimate the following OLS regression,[6] where the set of explanatory variables is made of our direct measures of financial sophistication and control variables:

$$\begin{aligned} DE_i = \alpha + \beta_1 Gender_i + \beta_2 Age\_2012_i + \beta_3 Log(number\_stocks)_i \\ +\beta_4 Log(number\_markets)_i + \beta_5 Log(number\_trades)_i \\ +\beta_6 Funds\_trader_i + \beta_7 Number\_day\_trades_i \\ +\beta_8 Number\_stop\_loss\_orders_i + \varepsilon_i \end{aligned} \tag{4.1}$$

All the variables were presented in tables 1 and 2. According to the literature, we expect that the DE is negatively related to all of our sophistication proxies.

4.2 Hypothesis 2: Financial literacy assessed through the A-test has an impact on the DE

In order to test this second hypothesis, we estimate the following OLS regression, where the set of explanatory variables is made of measures of financial sophistication *assessed* through the A-test:

$$\begin{aligned} DE_i = \alpha + \beta_1 Financial\_markets\_knowledge_i \\ +\beta_2 Highest\_education\_degree_i + \beta_3 Number\_orders\_year_i \\ +\beta_4 Investment\_advice_i + \varepsilon_i \end{aligned} \tag{4.2}$$

The first three explanatory variables were presented in table 3.
The $Financial\_markets\_knowledge$ variable allows us to check whether there is a link between the perception an investor has of his market knowledge and his DE. A higher self-

[6] We study cross-sectional variations in the DE among investors with different characteristics and "pool" the $DE_{i,s}$ to compute a DE for each investor, DE_i. It is important to notice that the computation of the DE at an individual level implies that the PGR and PLR measured for an investor is independent from the PGR and PLR computed for the other investors.

estimated market knowledge is expected a priori to be associated with a lower DE. The $Highest\_education\_degree$ variable allows to determine whether there is a significant relationship between the education level and the DE. Building on Dhar and Zhu (2006) who show a significant relationship between professional occupation and the DE, we expect that the most educated investors are less prone to the DE. The $Number\_orders\_year$ variable allows us to test whether trading activity impacts the level of DE, similarly to the $Log(number\_trades)$ variable in the first hypothesis. However, the variable used here is an estimate, depending on the investor's perception.

To complement the set of explanatory variables, we add the $Investment\_advice$ variable, which is a dummy that takes the value of 1 if the retail investor asked for investment advice and 0 otherwise. This allows us to investigate whether investment advice provided by the investment firm to their clients has an impact on their DE.

4.3 Hypothesis 3: Investor profile and personal traits determined through the S-test have an impact on the DE

In order to test this third hypothesis, we estimate the following OLS regression, where the set of explanatory variables is made of investment profile and personal traits characterized through the S-test:

$$\begin{aligned} DE_i = \alpha + \beta_1 Tendency\_loss\_not\_realization_i + \beta_2 Expertise\_self\_evaluation_i \\ + \beta_3 User\_profile_i + \varepsilon_i \end{aligned} \tag{4.3}$$

The first explanatory variable ($Tendency\_loss\_not\_realization$) is built on a specific question regarding the decision investors would take if they face a sharp loss. This item is in fact a measure of the tendency for a investor to not realize important losses (from 1 to 5). Therefore this variable allows us to relate this perception measure of loss realization to the DE. Intuitively, we expect that retail investors who declare a high tendency to not realize losses are more prone to the DE.

As for the $Expertise\_self\_evaluation$ variable, it is based on answers given by investors regarding their self-estimated level of knowledge and experience about risks and potential obligations inherent to different types of instruments (from 0 (no knowledge) to 2 (good knowledge)). This variable allows us to determine whether there is a link between the self-estimated expertise of an investor and his DE. Assuming investors are able to correctly estimate their expertise, we expect that a higher self-estimated expertise is associated with a lower DE.

The last variable refers to the $User\_profile$, which depends on the total score to the S-test (see table 4).

4.4 Hypothesis 4: Time and market conditions have an impact on the DE

With this fourth hypothesis, we investigate whether time and market conditions have an impact on the investor's DE. For this purpose, we focus on the impact of the two recent financial crises covered in our sample period, that are the "internet bubble" crisis in the beginning of the 2000's as well as the "financial crisis" that has taken place since 2007.

In a preliminary stage, we conduct tests to determine whether we observe, at a global level, a change in investors' behavior during the crisis periods relative to "normal" market conditions. To do so, we compute the DE of the aggregate investor before and after the 2008 financial crisis.[7]

In a second stage, we develop a panel data regression model with time-fixed effect, which takes into account both cross-sectional and time-varying dimensions of the DE. For this purpose, we compute a DE for each investor i and for each year t ($DE_{i,t}$) and regress them in a panel data model that incorporates the set of explanatory variables used in the first hypothesis (where some are now expressed in two dimensions, in function of the investor and time) and add N-1 dummy variables for the number of years in our sample period. To control for potential individual investors fixed effect, we cluster the panel data regression by investors. Indeed, to deal with potential "firm" and/or "time" correlation in the error term, Petersen (2009) recommends to cluster by the two dimensions (in our case, the individual investors and the time dimension). However, when there are only a few clusters (in our case in the time dimension), Petersen (2009) states that clustering by the more frequent cluster (in our case the individual investors dimension) and adding dummies for the other dimension (in our case

[7] Due to a lack of data before the beginning of the 2000's, we are not able to perform the same analysis for the internet bubble crisis.

the time dimension) yields results that are almost identical to clustering by both dimensions. The model to be estimated is then the following:

$$
\begin{gathered}
DE_{i,t} = \alpha + \beta_1 Gender_i + \beta_2 Age_{i,t} + \beta_3 Log(number\_stocks)_{i,t} \\
+\beta_4 Log(number\_markets)_{i,t} + \beta_5 Log(number\_trades)_{i,t} \\
+\beta_6 Funds\_trader_i \\
+\beta_7 Number\_day\_trades_{i,t} \\
+\beta_8 Number\_stop\_loss\_orders_{i,t} \\
+\beta_9 Year\_2000 + \beta_{10} Year\_2001 + \beta_{11} Year\_2002 \\
+\beta_{12} Year\_2003 + \beta_{13} Year\_2004 \\
+\beta_{14} Year\_2006 + \beta_{15} Year\_2007 \\
+\beta_{16} Year\_2008 + \beta_{17} Year\_2009 + \beta_{18} Year\_2010 \\
+\beta_{19} Year\_2011 + \beta_{20} Year\_2012 + \sum_{\gamma=2}^{51098} \gamma_i * S_i + \varepsilon_{i,t}
\end{gathered}
\tag{4.4}
$$

We should mention that we have chosen 2005 as the reference year, since it is after the internet bubble crisis and before the financial crisis.

Consistent with the literature, we expect time and market conditions, especially during crisis periods, to play a significant role in the variation of the DE. However, no consensus arises about how market conditions influence the DE because of conflicting empirical results. As mentioned earlier, Leal et al. (2006) find that this bias is much more pronounced during bullish periods while Cheng et al. (2013) draw the opposite conclusion.

4.5 Hypothesis 5: The type of stock traded (financial or not) has an impact on the DE

With this last hypothesis, we investigate whether the type of stock traded may impact the DE. In other words, we test whether there is a stock-specific effect in addition to the individual effect driven by the investor's characteristics. In particular, we focus on a potential effect related to financial stocks, which are usually said to behave differently from others.

In order to check for a financial stock-specific effect, we compute a DE for each investor i and for each stock s ($DE_{i,s}$) and regress them in the model below, which includes the set of explanatory variables used in hypothesis 1 (where some are now expressed in function both of the investor and of the type of stock traded) and a dummy that differs from zero when the stock traded is a financial one. To control for potential individual investors-fixed effect, we cluster the panel data regression by investors as we did in Hypothesis 4. The model to be estimated is the following:

$$\begin{gathered} DE_{i,s} = \alpha + \beta_1 Gender_i + \beta_2 Age\_2012_i + \beta_3 Log(number\_stocks)_i \\ +\beta_4 Log(number\_markets)_i + \beta_5 Log(number\_trades)_{i,s} \\ +\beta_6 Funds\_trader_i + \beta_7 Number\_daytrades_{i,s} \\ +\beta_8 Number\_Stop\_loss\_orders_{i,s} + \beta_9 Financial\_stock + \sum_{\gamma=2}^{51098} \gamma_i * S_i + \varepsilon_{i,s} \end{gathered} \tag{4.5}$$

Based on Ranguelova (2001), we expect stock characteristics to play a significant role in the variation of the DE besides investors' characteristics. In particular, we expect the behavior of a given investor towards financial stocks to be different relative his behavior towards stocks from other sectors. This expectation is built on both the well-established particularity of financial stocks and their exposure to market conditions during the period under scrutiny. However, we may expect the financial stock-effect to depend on time. Because of the dramatic underperformance of financial stocks during the financial crisis, we expect the financial stock-specific effect to differ before and after 2008.

5 Empirical work

We review in this section all the empirical results.

5.1 Evidence of DE at the aggregate level

Table 5 reveals that the average investor in our sample displays a positive and highly significant DE. In particular, he realizes 3.41% more his gains than his losses. Accordingly, a "winner" stock has about 1.5 ($\overline{PGR}/\overline{PLR}$) more chance to be sold than a "loser" stock. This result is in line with the extant literature, e.g. Barber et al. (2007) who documents a DE of 2.72%. We should also point out that around 23% of the investors display the Reverse DE, which is consistent with the findings of Dhar and Zhu (2006) or Boolell-Gunesh et al. (2012).

Table 5: DE at the aggregate level

Variable	Mean	Std Dev	t-value	p-value
PGR	10.12%	22.90%	30.86	<.0001
PLR	6.71%	20.98%	99.88	<.0001
DE	3.41%	24.98%	72.30	<.0001

The table reports descriptive statistics for the Proportion of Gains Realized (PGR), the Proportion of Losses Realized (PLR) and the DE, computed across our 51 098 sample investors over the period 1999-2012. t-values and p-values are also provided for the Student distribution with n-1 degrees of freedom testing the null hypothesis that the variable is significantly different from zero.

5.2 Hypothesis 1: Financial literacy measured by direct proxies has an impact on the DE

Table 6 reports the parameter estimates as well as their significance for the regression 4.1. By contrast to some previous studies, both gender and age seem to play no significant role in the DE variation. As for diversification measured through either the number of different stocks or markets, it is negatively related to the DE, suggesting diversification is associated with financial sophistication as expected.

We observe that a higher number of trades is positively related to the DE. It seems counter-intuitive at the first sight as we assume that retail investors who trade frequently become more familiar with financial markets and thus more experienced traders. However, we may also argue that, if the average investor exhibits the DE (as proven in table 5), he tends to realize more his gains than losses and consequently realize more winning trades than losing trades. As a result, the $Log(number\_trades)$ variable may content more winning trades that losing trades in proportion. This phenomenon could explain why we find out the higher the number of trades, the higher the DE level.

As expected, the DE of retail investors who are used to make more sophisticated trades (investment fund shares trading) is significantly lower. Retail investors associated with a more frequent and a more expert trading activity (day traders) also exhibits a significantly lower DE, which is consistent with Odean (1998) who shows that frequent traders display a lower DE. Furthermore, we find empirical evidence of Shefrin (2007)'s suggestion: the use of stop-loss orders allows investors to cut more rapidly their losses and help them dampen the DE.

Although the adjusted R^2 is weak, it is in line with the previous empirical studies. Variance Inflation Factor (VIF) is provided in table 16 available in appendix.

Table 6: Hypothesis 1 results

Variables	Parameter Estimates
Intercept	3.36(***)
Gender	-0.27
Age_2012	0.0031
Log(number_stocks)	-5.22(***)
Log(number_markets)	-0.62(*)
Log(number_trades)	4.17(***)
Funds_trader	-0.44(*)
Number_day_trades	-0.01(***)
Number_stop_loss_orders	-0.08(***)
Adjusted R^2	1.01%

The table reports the parameter estimates for the regression 4.1. *Gender* is a binary variable which equals 1 for men. *Age_2012* is computed using the date of birth of each retail investor. *Log(number_stocks)* is the log of the number of different stocks traded during the sample period. *Log(number_markets)* is the log of the number of different markets in which a retail investor has submitted at least an order. *Log(number_trades)* is the log of the number of trades executed. *Funds_trader* is a binary variable that takes the value of 1 if the retail investor traded at least once investment fund shares. *Number_day_trades* is the number of daily roundtrips executed over the entire period. *Number_stop_loss_orders* is the number of stop-loss orders used by the investor. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

5.3 Hypothesis 2: Financial literacy assessed through the A-test has an impact on the DE

Table 7 reports the parameter estimates as well as their significance for the regression 4.2.[8] Consistent with our expectations, the perception of a higher financial markets knowledge and a higher education degree are associated with a lower DE. In addition, the result for the number of orders is in line with what we find for the number of trades in hypothesis 1. All in all, the findings using A-test items are consistent with the results obtained for the corresponding direct proxies of sophistication. This suggests that A-test seems to be really informative to characterize investors and their exposure to the DE.

[8] VIF are provided in table 17 available in appendix.

We find also that investors who asked for investment advice display a significantly lower DE, thereby suggesting that investment firms help their clients to reduce this behavioral bias. This result brings support for MiFID attempt to increase retail investors' protection.

Table 7: Hypothesis 2 results

Variables	Parameter Estimates
Intercept	4.438(***)
Financial_markets_knowledge	-0.27812(**)
Highest_education_degree	-0.34893(*)
Number_orders_year	0.35322(***)
Investment_advice	-1.108(***)
Adjusted R^2	0.07%

The table reports the parameter estimates for the regression 4.2. *Investment_advice* is a dummy variable that takes the value of 1 if the retail investor asked for investment advice and 0 otherwise. *Financial_markets_knowledge* is a variable ranging from 0 to 3, with the level 0 being associated with a basic knowledge while the level 3 refers to an experienced investor who manages any aspect of the financial markets. *Number_orders_year* is another variable ranging from 0 to 3, with the level 0 being associated with zero order while the level 3 refers to more than 36 orders. *Highest_education_degree* is a variable ranging from 0 to 2: the level 0 corresponds to no degree, the level 1 to secondary or high school degree, and the level 2 to university or equivalent degree. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

5.4 Hypothesis 3: Investor profile and personal traits determined through the S-test have an impact on the DE

Table 8 reports the parameter estimates as well as their significance for the regression 4.3.[9] We find that retail investors who stated a large tendency to not realize loss display a significantly higher DE. Again, this result brings support for the S-test relevance. It seems to be useful for investment firms as well as for regulators in their concern to characterize investors and provide them with suitable services in a protection perspective.

As for the self-evaluation of an investor's own expertise on financial instruments, the result is not consistent with the previous ones and with our expectation. Maybe it is an evidence of overconfidence, which leads investors to overestimate their own expertise in the S-test.

[9] VIF are provided in table 18 available in appendix.

Finally, table 8 shows that a more aggressive investment profile is significantly related to a lower DE. Basically, it means that investors characterized as ”aggressive” or ”dynamic” through the S-test are less subject to the DE, in comparison to ”neutral” or ”conservative” investors. This result is not really surprising since the S-test tends to associate more aggressive profiles with a higher financial sophistication. This confirms again the relevance of such a test to infer the exposure to the DE.

Table 8: Hypothesis 3 results

Variables	Parameter Estimation
Intercept	1.83(**)
Tendency_loss_not_realization	0.49(***)
Expertise_self_evaluation	0.49(*)
User_profile	-0.53(*)
Adjusted R^2	0.05%

The table reports the parameter estimates for the regression 4.3. *Tendency_loss_not_realization* is a variable built on a specific question regarding the decision investors would take if they face a sharp loss. It delivers a measure of the tendency for a investor to not realize important losses, ranging from 1 to 5. *Expertise_self_evaluation* is a variable based on answers given by investors regarding their self-estimated level of knowledge and experience about risks and potential obligations inherent to different types of instruments. It ranges from 0 (no knowledge) to 2 (good knowledge). *User_profile* is a variable that depends on the total score to the S-test, resulting in one of the four possible investment profiles: conservative, neutral, dynamic, or aggressive. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

5.5 Hypothesis 4: Time and market conditions have an impact on the DE

Table 9 exhibits the DE for the aggregate investor before and after the 2008 crisis. We find that in the post-2008 period, the aggregate investor still displays the DE but at a significantly lower level than before 2008. Specifically, the DE decrease seems to be mainly driven by the PGR decrease and suggests that in downturn periods, investors are less prone to realize their gains. These findings are consistent with Leal et al. (2006) who document that when markets are falling, ”winner” stocks appear to be good choice, which reinforces investors’ confidence to keep them during a longer period.

Table 9: Hypothesis 4 results - DE for the aggregate investor before and after 2008

	Before 2008	After 2008	p-value
PGR	6.40	4.17	<.0001
PLR	2.97	2.72	0.0153
DE	3.42	1.44	<.0001

The table reports the Proportion of Gains Realized (PGR), the Proportion of Losses Realized (PLR), the DE computed across our 51 098 sample investors over the two subperiods over scrutiny as well as the p-values associated to the null hypothesis that variables before and after 2008 are different.

For robustness check, we replicate the analysis by taking into account only the investors who trade both before and after the 2008 financial crisis (24 735 investors). The corresponding results are displayed in table 10. We observe the similar phenomenon, even though a decrease in the PLR arises too.

Table 10: Hypothesis 4 results - DE for the investors who trade both before and after 2008

	Before 2008	After 2008	p-value
PGR	6.88	3.97	<.0001
PLR	3.19	2.66	<.0001
DE	3.69	1.30	<.0001

The table reports the Proportion of Gains Realized (PGR), the Proportion of Losses Realized (PLR), the DE computed across our 24 735 sample investors over the two subperiods over scrutiny as well as the p-values associated to the null hypothesis that variables before and after 2008 are different.

Table 11 reports the parameter estimates as well as their significance for the regression 4.4. These findings allow us to identify a significant and negative time-fixed effect during the crisis periods (in 2000 and especially since 2007). In the opposite, we observe an increase in the DE in the bullish period (2003 and 2004) in comparison to "normal" market conditions.

These results also confirm our previous findings, suggesting the robustness of the static model used to test hypothesis 1. Most of the results remain significant in the dynamic model. One exception is the $Log(number\_markets)$ variable that becomes significantly positive. This result might be linked to the wave of fragmentation in the European trading landscape due to

MiFID. Furthermore, gender and age seem now to play a significant role in the investor's DE variation. Men and older investors appear to be less prone to the DE over time, which is in line with the findings in Boolell-Gunesh et al. (2012).

Table 11: Hypothesis 4 regression results

Variables	Parameter Estimates
Intercept	2.97(***)
Gender	-0.39(**)
Age	-0.019(***)
Log(number_stocks)	-3.30(***)
Log(number_markets)	0.61(***)
Log(number_trades)	3.72(***)
Funds_trader	-0.84(***)
Number_day_trades	-0.075(***)
Number_stop_loss_orders	-0.53(***)
Year_2000	-2.47(***)
Year_2001	0.28
Year_2002	1.19
Year_2003	1.34(***)
Year_2004	0.76(***)
Year_2006	-0.062
Year_2007	-1.72(***)
Year_2008	-1.50(***)
Year_2009	-1.21(***)
Year_2010	-1.89(***)
Year_2011	-3.06(***)
Year_2012	-0.43(***)
Adjusted R^2	0.71%

The table reports the parameter estimates for the regression 4.4. *Gender* is a binary variable which equals 1 for men. *Age* is computed using the date of birth of each retail investor. *Log(number_stocks)* is the log of the number of different stocks traded during the sample period. *Log(number_markets)* is the log of the number of different markets in which a retail investor has submitted at least an order. *Log(number_trades)* is the log of the number of trades executed. *Funds_trader* is a binary variable that takes the value of 1 if the retail investor traded at least once investment fund shares. *Number_day_trades* is the number of daily roundtrips executed. *Number_stop_loss_orders* is the number of stop-loss orders used by the investor. 2005 is the reference year. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

5.6 Hypothesis 5: The type of stock traded (financial or not) has an impact on the DE

Table 12 reports the parameter estimates as well as their significance for the regression 4.5. We observe a significant and positive financial stock-fixed effect. However, this result may be explained by the fact that investors who trade financial stocks are different (have a different trading style) from investors who trade other types of stocks. Investors who trade financial stocks may simply display a higher DE in comparison to other investors. In that perspective, the type of stock traded would'nt play any role in the DE variation.

Table 12: Hypothesis 5 results

Variables	Parameter Estimates
Intercept	2.16(***)
Gender	-0.27(***)
Age_2012	-0.01(***)
Log(number_stocks)	-0.11
Log(number_markets)	-0.20
Log(number_trades)	1.19(***)
Funds_trader	-0.48(***)
Number_day_trades	-0.14(***)
Number_stop_loss_orders	-3.13(***)
Financial_stock	0.53(***)
Adjusted R^2	0.43%

The table reports the parameter estimates for the regression 4.5. *Gender* is a binary variable which equals 1 for men. *Age_2012* is computed using the date of birth of each retail investor. *Log(number_stocks)* is the log of the number of different stocks traded during the sample period. *Log(number_markets)* is the log of the number of different markets in which a retail investor has submitted at least an order. *Log(number_trades)* is the log of the number of trades executed. *Funds_trader* is a binary variable that takes the value of 1 if the retail investor traded at least once investment fund shares. *Number_day_trades* is the number of daily roundtrips executed. *Number_stop_loss_orders* is the number of stop-loss orders used by the investor. *Financial_stock* is a dummy variable that equals 1 when the stock belongs to the financial sector and 0 otherwise. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

To control for investors' characteristics, we build on Ranguelova (2001)[10] and replicate our analysis only on investors who trade both financial stocks and other types of stocks (6 675 investors). Results are reported in table 13, where we observe that the financial stock-specific effect remains significantly positive.

Table 13: Hypothesis 5 results - restricted sample

Variables	Parameter Estimations
Intercept	2.76(***)
Gender	-0.09
Age_2012	-0.02(***)
Log(number_stocks)	0.05
Log(number_markets)	-0.28
Log(number_trades)	0.81(***)
Funds_trader	-0.58(***)
Number_day_trades	-0.09 (***)
Number_stop_loss_orders	-3.73(***)
Financial_stock	0.47(***)
Adjusted R^2	0.43%

The table reports the parameter estimates for the regression 4.5. *Gender* is a binary variable which equals 1 for men. *Age*_2012 is computed using the date of birth of each retail investor. *Log*(*number_stocks*) is the log of the number of different stocks traded during the sample period. *Log*(*number_markets*) is the log of the number of different markets in which a retail investor has submitted at least an order. *Log*(*number_trades*) is the log of the number of trades executed. *Funds_trader* is a binary variable that takes the value of 1 if the retail investor traded at least once investment fund shares. *Number_day_trades* is the number of daily roundtrips executed. *Number_stop_loss_orders* is the number of stop-loss orders used by the investor. *Financial_stock* is a dummy variable that equals 1 when the stock belongs to the financial sector and 0 otherwise. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

Finally, since financial stocks were especially affected during the financial crisis, we replicate our analysis on both subperiods: before and after 2008. In that way, we control for time and market conditions. Tables 14 and 15 exhibit the corresponding results.

We still find a significant financial stock-specific effect. These findings suggest that, for a given investor, the DE for financial stocks is different from the DE for other types of stocks. In other words, the exposure to this behavioral bias depends on the stock: when trading financial

[10] To identify a relationship between the market capitalization and the DE, she restricts her analysis only on investors who trade stocks in both the top and bottom size quintile of market capitalization.

stocks, the behavior changes, even after controlling for market conditions. Not only investor's characteristics but also stock characteristics are drivers of the DE. However, the direction of the financial stock- specific effect depends on the period. Before the crisis, it seems that investors are more prone to the DE for financial stocks relatively to other types of stocks. By contrast, in the post-crisis period, they seem to be less subject to DE when trading financial stocks in comparison to other stocks. In particular, it seems that the DE variation over time (decrease during bearish periods and increase during bullish periods) is exacerbated when it comes to financial stocks. Our results provide support for Ranguelova (2001) who questions the Prospect Theory as the single origin of the DE.[11]

Table 14: Hypothesis 5 results - restricted sample before 2008

Variables	Parameter Estimations
Intercept	2.23(***)
Gender	-0.32(**)
Age_2012	-0.01(***)
Log(number_stocks)	-0.27(***)
Log(number_markets)	0.18
Log(number_trades)	1.42(***)
Funds_trader	-0.35(***)
Number_day_trades	-0.17(***)
Number_stop_loss_orders	-2.85(***)
Financial_stock	0.24 (*)
Adjusted R^2	0.52%

The table reports the parameter estimates for the regression 4.5. *Gender* is a binary variable which equals 1 for men. *Age_*2012 is computed using the date of birth of each retail investor. *Log*(*number_stocks*) is the log of the number of different stocks traded during the sample period. *Log*(*number_markets*) is the log of the number of different markets in which a retail investor has submitted at least an order. *Log*(*number_trades*) is the log of the number of trades executed. *Funds_trader* is a binary variable that takes the value of 1 if the retail investor traded at least once investment fund shares. *Number_day_trades* is the number of daily roundtrips executed. *Number_stop_loss_orders* is the number of stop-loss orders used by the investor. *Financial_stock* is a dummy variable that equals 1 when the stock belongs to the financial sector and 0 otherwise. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

[11] According to the Prospect Theory, behavioral biases should only be driven by investors' characteristics and a relationship between individual investors' DE and the type of stock traded should not exist. It means that for one single investor, the DE computed for a specific type of stock should be the same as the DE computed for other type of stock.

Table 15: Hypothesis 5 results - restricted sample after 2008

Variables	Parameter Estimations
Intercept	2.24(***)
Gender	-0.21(**)
Age_2012	-0.01(***)
Log(number_stocks)	-0.20 (***)
Log(number_markets)	-0.18
Log(number_trades)	0.68(***)
Funds_trader	-0.39(***)
Number_day_trades	-0.08(***)
Number_stop_loss_orders	-1.76(***)
Financial_stock	-0.28(***)
Adjusted R^2	0.27%

The table reports the parameter estimates for the regression 4.5. *Gender* is a binary variable which equals 1 for men. *Age_2012* is computed using the date of birth of each retail investor. *Log(number_stocks)* is the log of the number of different stocks traded during the sample period. *Log(number_markets)* is the log of the number of different markets in which a retail investor has submitted at least an order. *Log(number_trades)* is the log of the number of trades executed. *Funds_trader* is a binary variable that takes the value of 1 if the retail investor traded at least once investment fund shares. *Number_day_trades* is the number of daily roundtrips executed. *Number_stop_loss_orders* is the number of stop-loss orders used by the investor. *Financial_stock* is a dummy variable that equals 1 when the stock belongs to the financial sector and 0 otherwise. *Significant at the 10% level, **Significant at the 5% level, ***Significant at the 1% level.

6 Concluding Remarks

In this paper, we report an in-depth analysis of the DE both across individual investors and over time, and we contribute to the literature on several aspects.

First, we provide additional results about the relationship between investor's sophistication and the DE. The data at hand allow us to address in great detail the link between the investor's profile and his DE. Building on Boolell-Gunesh et al. (2012), we extend the range of direct sophistication proxies and examine new variables that are significantly related to the DE level such as the type of orders. In addition, we also use the answers to some MiFID tests items. Our main results reveal that sophistication, either directly observed or assessed through MiFID tests, helps investors reduce this behavioral bias. First, investors who are aware of diversification benefits and involved either in a more risky trading strategy (day trading) or in a more sophisticated investment choice (investment fund shares trading) exhibit a significantly lower DE. Second, we identify the use of stop-loss orders as an effective tool for investors to dampen their DE. We also find that a perception of better financial market knowledge and a higher education degree are both negatively related to the DE. Furthermore, investors who asked for investment advice are associated with a significantly lower DE, which suggests that investment firms reduce their clients' exposure to this behavioral bias. We also bring evidence that some personal traits play a role in the exposure to the DE. In particular, retail investors who stated a large tendency to realize sharp losses or investors qualified as "aggressive" through the Suitability test display a significantly lower DE.

All in all, the findings based on the MiFID tests are consistent with the results obtained for direct proxies of sophistication. We bring empirical evidence of their relevance and usefulness to characterize investors and their exposure to the DE. These results are particularly interesting for investment firms as well as for regulators in their concern to characterize investors and provide them with suitable services in a protection perspective.

Another contribution is related to our sample period that is large and recent (1999-2012), which allows us to take into account the temporal dimension of the DE and the impact of recent crisis periods (such as the internet bubble and the 2008 financial crisis). By contrast to "normal" market conditions, we document that the aggregate investor seems to display a significantly lower DE when markets are falling while he exhibits the highest DE when markets are booming such as in the mid 2000's. In downturn periods, investors seem to be less prone to realize their gains.

Finally, we also examine the relationship between the type of stock traded and the DE. We identify a financial stock-specific effect, even after controlling for investor's characteristics. Basically, for a given investor, the DE on financial stocks is significantly different from the DE on other types of stocks. More precisely, we observe that the DE variation over time (decrease during bearish periods and increase during bullish periods) is exacerbated when focusing on financial stocks. These findings suggest that stock characteristics are additional drivers of this behavioral bias.

References

Barber, B. M., Y.-T. Lee, Y.-J. Liu, and T. Odean (2007). Is the aggregate investor reluctant to realise losses? evidence from taiwan. *European Financial Management 13*(3), 423–447.

Boolell-Gunesh, S., M. Broihanne, and M. Merli (2012). Sophistication of individual investors and disposition effect dynamics. *Finance 33*(1), 9–371.

Cheng, T., C. Lee, and C. Lin (2013). An examination of the relationship between the disposition effect and gender, age, the traded security, and bull bear market conditions. *Journal of Empirical Finance 21*, 195–213.

Dhar, R. and N. Zhu (2006). Up close and personal: An individual level analysis of the disposition effect. *Management Science 52*(5), 726–740.

Feng, L. and M. S. Seasholes (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance 9*(3), 305–351.

Frazzini, A. (2006). The disposition effect and underreaction to news. *The Journal of Finance 61*(4), 2017–2046.

Grinblatt, M. and B. Han (2005). Prospect theory, mental accounting, and momentum. *Journal of financial economics 78*(2), 311–339.

Grinblatt, M. and M. Keloharju (2001). What makes investors trade? *The Journal of Finance 56*(2), 589–616.

Hur, J., M. Pritamani, and V. Sharma (2010). Momentum and the disposition effect: the role of individual investors. *Financial Management 39*(3), 1155–1176.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263–291.

Lakonishok, J. and S. Smidt (1986). Volume for winners and losers: Taxation and other motives for stock trading. *The Journal of Finance 41*(4), 951–974.

Leal, C., M. Armada, and J. Duque (2006). New evidences on the disposition effect of individual investors. *Faculade de Economia da Universidade do Porto Working Paper*, 1–30.

Linnainmaa, J. (2010). Do limit orders alter inferences about investor performance and behavior? *Journal of Finance 65*(4), 1473–1506.

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of finance 53*(5), 1775–1798.

Oehler, A., K. Heilmann, V. Läger, and M. Oberländer (2003). Coexistence of disposition investors and momentum traders in stock markets: experimental evidence. *Journal of International Financial Markets, Institutions and Money 13*(5), 503–524.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of financial studies 22*(1), 435–480.

Ranguelova, E. (2001). Disposition effect and firm size: New evidence on individual investor trading activity. *Working Paper*.

Shefrin, H. (2007). Beyond greed and fear: understanding behavioral finance and the psychology of investing. *Oxford University Press*.

Shefrin, H. and M. Statman (1984). The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance 40*(3), 777–790.

Statman, M., S. Thorley, and K. Vorkink (2006). Investor overconfidence and trading volume. *Review of Financial Studies 19*(4), 1531–1565.

Subrahmanyam, A. (2007). Behavioural finance: A review and synthesis. *European Financial Management 14*(1), 12–29.

Talpsepp, T. (2011). Reverse disposition effect of foreign investors. *Journal of Behavioral Finance 12*(4), 183–200.

Thaler, R. (1985). Mental accounting and consumer choice. *Marketing science 4*(3), 199–214.

Weber, M. and C. F. Camerer (1998). The disposition effect in securities trading: An experimental analysis. *Journal of Economic Behavior & Organization 33*(2), 167–184.

Appendix

Table 16: Hypothesis 1 VIF results

Variables	VIF
Intercept	0
Gender	1.02
Age_2012	1.09
Log(number_stocks)	12.75
Log(number_markets)	4.95
Log(number_trades)	8.48
Funds_trader	1.09
Number_day_trades	1.11
Number_stop_loss_orders	1.03

Table 17: Hypothesis 2 VIF results

Variables	VIF
Intercept	0
Financial_markets_knowledge	1.30
Highest_education_degree	1.01
Number_orders_year	1.24
Investment_advice	1

Table 18: Hypothesis 3 VIF results

Variables	VIF
Intercept	0
Tendency_loss_not_realization	1.29
Expertise_self_evaluation	1.32
User_profile	1.58