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THE DISPOSITION EFFECT AMONG MUTUAL FUND PARTICIPANTS: A RE-EXAMINATION

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Abstract

Using information on mutual fund trades executed from 1998 to 2017 by 31,513 individual investor clients of a major Portuguese financial institution, we study the relationship between the disposition effect, financial literacy and trading experience. We find that mutual fund investors exhibit strong disposition effect. The tendency to hold losers is partially offset with literacy: not only holding a university degree reduces the propensity to hold on to loser funds but also higher financial knowledge and stronger math skills reduce the disposition effect. Literacy also plays a role in shaping the way experience affects this bias. Evidence of the disposition effect persists after accounting for redemption fees, bad emotions, irrational beliefs, market sentiment and the existence of someone to blame.

JEL classification: G11; G41; G53
Keywords: disposition effect; mutual funds; financial literacy

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1. Introduction

Do participants[1] in mutual funds exhibit disposition effect? Is this behavioral bias attenuated by financial literacy or trading experience? Using a novel proprietary database from a major Portuguese financial institution containing transaction-level records for a twenty-year span, we attempt to answer to these questions.

In the last decades, behavioral finance has challenged the traditional view that financial assets are rationally priced and reflect all available information. Accordingly, certain market anomalies could be explained with the presence of individual investors' irrational behavior (e.g., Benartzi and Thaler 1995). Amid the innumerous biases that have been underlined by behavioral economists, the disposition effect brought forward by Shefrin and Statman (1985) stands out. In short, the disposition effect is characterized by a higher propensity of investors to sell assets on which they have experienced gains and to hold assets on which they have faced (unrealized) losses. The existence of this behavioral bias may have relevant welfare implications because it imposes substantial costs on investors. As highlighted by Kaustia (2010), the disposition effect imposes a higher tax-burden than necessary for individual investors. Moreover, it may interfere with forward-looking decision making, thereby inducing inferior performance (Goetzmann and Massa 2008).

There is already a bulk of empirical evidence pointing towards the existence of disposition effect in the stock trading patterns of individual investors. Grinblatt and Keloharju (2001) document disposition effect in a sample of investors from Finland. Odean (1998) finds that US investors tend to sell stocks whose prices increased and to hold losers. Feng and Seasholes (2005) and Chen et al. (2004) find disposition effect among Chinese investors. Barber and Odean (2007) find disposition effect for individual and institutional investors in Taiwan, with individuals displaying the strongest disposition effect. Brown et al. (2006) uncover weaker disposition effect for traders making large trades in Australia. While conducting an experiment, Weber and Camerer (1998) also show that individuals are more likely to sell winners than losers. Frazzini (2006) reports that mutual funds sell equities held for a gain at a higher rate than those held for a loss, being this tendency stronger following years of poor fund performance.

In contrast with the stock market, little attention has been paid to the disposition effect among mutual fund participants. Nevertheless, understanding the role of this

[1] We use the terms "mutual fund participants" and "mutual fund investors" interchangeably in this study.

behavioral bias in the context of mutual fund participants is relevant for several reasons. In fact, regardless of the financial instrument, the existence of the disposition effect imposes costs on investors. Individual investors have been shifting their investment strategies from a direct exposure to the stock market through individual stocks to an indirect exposure via mutual funds (Boehmer and Kelley 2009). Thus, if this behavioral bias is weaker (stronger) in mutual fund trading activity then individual investors have lower (higher) costs when they invest relatively more in mutual funds than in stocks. Second, the existence of disposition effect leads to less efficient markets and the eventual inexistence of this bias in mutual fund investments may contribute to more efficient financial markets given the higher relevance of the assets under management of mutual funds.

Finally, there are important consequences for the mutual funds industry if investors exhibit disposition effect. On the downside, the disposition effect may have implications in terms of the relationship between participants (the principal) and fund managers (the agent). The existence of disposition effect in this market diminishes individual investors’ reaction to poor performance and thus distorts market discipline mechanisms. In essence, managers will face lower pressure if investors do not respond to poor performance and remain attached to losing funds. Hence, managers will have fewer incentives in pursuing the interests of their clients. Measuring the disposition effect and its impact is thus useful in understanding market dynamics.

On the upside, the presence of disposition effect among mutual fund participants may have important implications in terms of the liquidity risk of the fund. If the performance of the fund plunges, it is unlikely that investors displaying disposition effect will exert abnormal outflow pressure. This diminishes the liquidity needs of the mutual fund and attenuates the need to carry out fire sales.

The conclusions of existing studies for mutual funds conflict with those obtained for the stock market, particularly in the US. Ivković and Weisbenner (2009) obtain results that conform to the idea that the disposition effect does not affect mutual fund participants in the US. These results are, in general, consistent with those of Bailey, Kumar, and Ng (2011), who show that US mutual fund investors are, on the aggregate, more sophisticated than those that trade only stocks. Calvet, Campbell, and Sodini (2009a) do not find evidence of disposition effect among Swedish mutual fund participants. Related research on the flow-performance relationship (Ferreira et al. 2012) reveals substantial differences across countries, and also that mutual fund investors tend to sell losers more and to buy winners less in more developed countries, meaning that US findings do not map directly onto other countries. For Portugal, Alves and Mendes (2011) find an absence of reaction to past performance and persistence of fund flows, which contrasts with the US experience.

Chang, Solomon, and Westerfield (2016) find evidence consistent with the notion that investors avoid realizing losses because they dislike admitting that past purchases were mistakes, but delegation reverses this effect by allowing the investor to blame the manager instead. Accordingly, the propensity to realize past gains more than past losses applies only to nondelegated assets like individual stocks; delegated assets, like mutual funds, exhibit a robust reverse-disposition effect. However, an alternative explanation is that behavioral biases may manifest differently across different asset classes or even amid different securities. In effect, this reasoning is aligned with the findings of Kumar (2009) that the disposition effect is more pronounced amid stocks that are more complex to value.

This study investigates the disposition effect among mutual fund investors using a sample of 31,513 investors of a major Portuguese financial institution in the period comprised between 1998 and February 2017. Our methodology lies on the Cox proportional hazard model and our findings hint at a strong disposition effect among mutual fund investors: the probability of a redemption ramps up more than 70 percentage points when the mutual fund is not trading at a loss.

In our second research question, we inquire whether financial literacy and trading experience weaken the disposition effect exhibited by mutual fund investors. Prior research indicates that investors' heterogeneity affects behavioral biases. For instance, experience and sophistication have been pointed out as moderators of the disposition effect (Feng and Seasholes 2005). Chen et al. (2004) and Choe and Eom (2009) also establish a negative link between trading experience and the disposition effect in a sample of Chinese and Korean investors, respectively. Shapira and Venezia (2001) find stronger disposition effect for independent stock market investors than for those advised by brokers in Israel. Dhar and Zhu (2006) find that around 20% of investors exhibit reverse disposition effect, active traders being more willing to accept losses.

We evaluate the role of literacy as a potential moderator of the disposition effect. We anticipate that individuals with higher levels of literacy will plausibly behave more rationally. General literacy, measured by the level of education, is "fundamental for obtaining a correct perception of financial information and available opportunities, as well as being crucial in the decision-making process" (Abreu and Mendes 2010, p.517).

We estimate our baseline model for two subsamples, one including investors holding a university degree and the other with the remaining individuals, and conclude that general literacy is a pervasive determinant of the disposition effect among mutual fund participants: the hazard ratio goes down by 44 percentage points when we move from the second to the first group.

There is another dimension of financial literacy which is not captured by the general level of education: the individual knowledge about financial markets and products (Abreu and Mendes 2010). Financially informed investors are aware of the existing financial options, choices and consequences, and thus are better positioned to increase their well-being. Considering that an individual who has a qualified occupation in the financial sector (banks, insurance, and brokerage firms), is a business consultant, auditor or economist is more knowledgeable about financial markets and products, our results fit well with the notion that higher financial literacy (or stronger math skills) also reduce the reluctance to sell losers or the propensity to sell winners.

We also assess the importance of trading experience as a moderator of the disposition effect. Our findings suggest that stock and bond trading initiation hardly affect the disposition effect, but derivative trading lessens the reluctance to redeem funds that are valued below purchase price. As to trading foreign financial instruments, it does not change the disposition effect exhibited by mutual fund participants. These results tell us that not all experience types help mitigate behavioral biases. In specific, experience in trading sophisticated financial instruments such as derivatives appears to produce greater effects in moderating the disposition effect than trading traditional securities such as stocks or bonds.

Next, we take the investigation a step forward and examine two distinct features of the trading background of mutual fund investors: trading intensity and diversity. Our results reveal that the number of buy trades and the turnover value of buy trades attenuate the disposition effect displayed by mutual fund investors, but the number of day trades performed by the participant does not appear to impact the size of the disposition effect. The number of different securities traded, and the number of different funds traded by the investor are used to measure diversity, and both measures lessen the disposition effect. When we consider the number of fund (buy) transactions, we find that, on average, mutual fund participants with more past fund transactions exhibit lower disposition effect.

We add piecewise linear components of the number of buy trades and corresponding turnover value to the baseline specification. Strikingly, we find that the disposition effect displayed by mutual fund participants with more than 20 buy trades is residual. If one considers instead adding piecewise linear components of the number of different securities traded, holding more than six different securities would also eliminate almost entirely the disposition effect. Most prominently, individuals with more than 30 (buy) transactions of mutual funds present a reverse disposition effect.

Finally, we appraise whether literacy boosts or attenuates the effect of experience on the disposition effect, and we find that the number of different funds, the number of different securities, the number of trades conducted in stock exchanges, and the turnover value generated by those trades attenuates the disposition effect of individuals with and without a university degree. Intriguingly, our findings suggest that day trading produces opposite effects on the disposition effect of individuals with and without financial literacy. In effect, while day trading reduces the disposition effect for those without financial literacy, those with financial literacy present a positive association between day trading and the disposition effect.

In supplementary tests, we consider alternative explanations for our findings, and our conclusions are preserved even after accounting for these alternative explanations. For instance, we examine whether irrational beliefs of investors on mean reversion patterns of fund returns could explain our findings. We find evidence consistent with irrational beliefs, but the disposition effect survives even after accounting for the existence of this bias. We also evaluate the effect of market sentiment on the results (we split the sample into bull and bear periods). While the disposition effect is statistically and economically significant during both periods, it is more sizable during bull periods.

In parallel, we gauge whether investors display lower disposition effect when there is someone to blame as in the case of delegated investments. Because the disposition effect is considerably larger for a subsample of funds that are more likely to being acquired after advice from the financial intermediary, we reject that hypothesis. Finally, we test whether bad emotions or redemption fees could be driving the results and find that the economic and statistical significance of the disposition effect still persists.

In sum, we present sound evidence that individual investors exhibit disposition effect in mutual fund trading. Our findings challenge the conclusions of Calvet, Campbell, and Sodini (2009a) and Ivković and Weisbenner (2009), who did not find evidence that mutual investors suffer from this bias. Moreover, our results reveal that the tendency to hold losers is partially offset with literacy. In effect, holding a university degree reduces the propensity to hold losers by 44 percentage points. In addition, trading intensity in funds reverts almost entirely the disposition effect.

The rest of the paper is structured as follows. Section 2 defines the variables and presents the methodology, whereas section 3 describes the sample. Section 4 discusses the results and section 5 draws final remarks.

2. Methodology

Our database consists of account-level proprietary data from a major Portuguese financial institution. The analysis is mostly concentrated on the tables containing transactions of securities and funds performed by the bank's clients. Those tables comprise data on the ISIN code of the security (fund) traded, the type of operation (buy/sell), the price and quantity traded, among other variables. We merge these tables with a dataset containing daily mutual fund prices from Bloomberg and Reuters.

To reduce the computational burden of estimations, our final dataset containing daily prices and transactions is converted into weekly frequency. The disposition effect is measured using the procedure put forward by Feng and Seasholes (2005), i.e., we run a survival analysis model where a "failure" occurs when the investor performs a redemption.[2] An investor is included in the final dataset when he/she opens a position in a mutual fund. In the wake of that event, the investor becomes at risk. For each week t after the first fund shares' subscription, the conditional probability (i.e., conditional on the position on the fund surviving in the portfolio up until week t-1) of redemption is estimated. Subsequent subscriptions (those after the initial buy) are considered holds given that the investor does, in fact, continues to hold the fund.

For each investor-fund-position-date in our sample, two types of comparisons are carried out. The first comparison involves actual redemption of fund's shares. When the investor redeems a share from a fund, we compare the redemption price with the original purchase price (the "reference price"). The share-weighted average purchase price is utilized as the reference price in this paper, specifically when multiple subscriptions take place before redemption.

[2] In robustness exercises, we follow Grinblatt and Keloharju (2001), and regress a holding indicator at the fund position level (1 = Redemption; 0 = Hold) on independent variables using Probit models. We reproduce all the major regressions using this methodology but, to conserve space, the results are not tabulated. Our conclusions do not change under this alternative econometric setting.

When there is no actual redemption, paper gains/losses are estimated. Paper gains occur when the share price weekly low is above its reference (purchase). The underlying rationale is that the investor could had redeemed his/her positions at any time during week t with a profit. Paper losses occur when the share price weekly low is below its reference (purchase price), whereby the investor could only had sold for a loss during that week.

Along the lines of Feng and Seasholes (2005), two different indicators are created. The trading profit indicator (TPI) takes a value of one if fund's shares are redeemed with a gain (or the shares are trading at a paper gain), and zero otherwise. The trading loss indicator (TLI) takes a value of one if fund's shares are redeemed for a loss (or the shares are trading at a paper loss). TPI and TLI vary over time. Since shares are either trading at a loss or at a gain (except in rare instances), we do not include TPI and TLI together in our regression models.[3]

In our baseline setting, a sell/hold variable (*SELL*) is regressed against the baseline hazard function and other "covariates" assuming the Cox proportional hazard model specification. Under this setting, the hazard rate assumes the following functional form:

$$\lambda(t|x) = \lambda_0(t) \times \exp^{\beta' x_t} \qquad [1]$$

where x is a vector of investor-specific independent variables, which may be 'fixed' or time-variant, and β is the vector of coefficients. The covariate vector can contain investor-demographic characteristics, literacy variables, experience and sophistication of the investor, or general market characteristics. Some variables can be interacted. The model estimates the proportional hazard rate, $\lambda_0(t|x)$, by multiplying the baseline hazard rate, $\lambda_0(t)$, with the relative hazard rate, $\exp^{\beta' x_t}$. Correspondingly, only the relative hazard rate is affected by the covariates. No assumptions are made about the baseline hazard rate aside from it being the same for all investors. The estimation is obtained using the maximum likelihood estimator.

A failure event takes place when a fund redemption occurs. Under the current setup an investor may have multiple failures. Intuitively, the time between the origin (the point where the investor becomes at risk) and each subsequent failure is estimated. In our

[3] The adoption of *TLI* rather than *TPI* as explanatory variable leads to identical conclusions, whereby the corresponding results are not tabulated.

most simple model specification, we regress the sell/hold variable on the baseline hazard function and TPI.

The next section proceeds with the definition of the variables and a description of the sample.

3. Data

The database contains three different tables covering the 20-year span from January 1998 to February 2017. The first table includes socio-demographic individual investor data, namely gender, occupation/job, education, country of residence, birth date, postal code, and binary variables (Yes/No) indicating whether the investor has savings account, consumer credit and mortgage. The second table displays all transaction-level records on securities operations (acquisitions and sales). This table contains the following variables: date of the transaction, type of transaction (buy or sell), quantity, price, currency, ISIN code of the security and security description. The third table encompasses mutual funds operations (over the counter subscriptions and redemptions). The table comprises information about the date of the transaction, type of transaction (subscription or redemption), number of shares, price, currency, ISIN code and fund name.

Several filters are applied. Records from non-residents are deleted and we drop clients that began their stock market activity and with experience in funds before January 1998. Our objective is to see whether experience influences behavioral biases, whereby we exclude all clients with previous experience in the stock market before beginning the assessment. We also exclude all closed-end funds and open-end money funds, real state funds and funds whose participants benefit from fiscal advantages[4], as well as funds that distribute dividends.

Next, we extract from Bloomberg and Reuters time series of the daily prices of the mutual funds in the database and match the panel of daily prices with the table of fund transactions. We keep all observations from the subscription date to the redemption date of a fund. Our final dataset contains 6,926,515 account/fund/date observations from 31,513 clients.

Several variables are added to the database. First, we add demographic variables such as the *gender* (female/male), investor *age* at the time of the first mutual fund

[4] In the earlier 2000's investors in PPR and PPA's were granted fiscal deductions based on the amount invested in the funds.

subscription, and education (three dummy variables: *educ0* takes the value of one for individuals displaying up to 12 years of education and zero otherwise; *educ1* takes the value of one for individuals displaying 12 or more years of education but have not completed a university degree and zero otherwise; *educ2* takes the value of one for individuals with a university degree and zero otherwise).

Literacy variables are built on the data from job/employment and education. Our more general variable of literacy is *educ2*. Financial literacy (*finlit*) and mathematical skills (*mathskills*) are binary variables, equal to one for individuals with higher education whose occupation hints at a high level of financial literacy (professionals from the banking sector, brokerage services, auditors, economists, certified accountants, financial directors), and for those with higher education whose occupation hints at a high level of mathematical skills (engineers, physicists, computer and data scientists, economists, financial managers), respectively.

Regarding the variables aimed at capturing the experience and financial sophistication of the investors, and given that we expect investors to learn with past experience, several dynamic variables reflecting the learning curve are created. *Equitytrader* and *bondtrader* are binary variables for which the value of one is assigned once the investor performs the first trade in stocks and bonds, respectively. These two variables translate the simplest interaction of the investor with the securities markets. *Derivativetrader*, *foreigntrader and daytrader* are binary variables set to one after the investor carries out the first trade in derivatives, foreign securities or day trade, respectively. These variables hint at a higher level of investor sophistication than simply trading a stock or a bond, since they entail more investor knowledge.

INSERT TABLE 1 ABOUT HERE

We include continuous variables in our regression models with the aim of capturing the impact of trading intensity and diversity on the disposition effect. The number of buy trades performed by the investor in securities markets (*numtrades*) and the corresponding trading value (*turnover*) capture general trading intensity. The number of day trades (*daytrading*) measures the effect of sophisticated traders' trading intensity on the disposition effect. The number of different securities (*diffsec*) and funds (*difffunds*) held in the past by the investor measure trading diversity, crude measures of diversification.[5] Finally, the number of fund (buy) operations (*numtradefunds*) is also used as a proxy for knowledge and experience about mutual funds.[6]

Table 2 presents descriptive statistics of the mutual fund participants included in the assessment. Around 37.5% of the investors live in one of the two major Portuguese cities (Lisbon and Oporto), and 61.5% of are male. Only a small percentage of investors have a consumer credit (3.3%) or a mortgage (7.0%), but 27.7% have a savings account. The level of scholarship of the individuals in our sample is low: most of the individuals with non-missing data have less than 12 years of education, and 13.8% of the individuals concluded a university degree. About 8.0% of the individuals are managers, and 7.6% have a qualified occupation (non-managers). The percentage of individuals with no occupation (unemployed, retired and others) hovers around 13.2%.

Only 4.0% had stock trading experience when they became at risk (8.0% when investors exit the sample). The percentage of investors that traded bonds before becoming at risk is around 1% (2% when investors exit the sample). The average cumulative number of (buy) operations in securities is 0.42 (1.03) per investor when investors become at risk (exit). The average cumulative turnover generated in securities markets per investor is 2,217 Euro when the investors become at risk (5,195 when leaving the sample). Most investors have no trades in securities markets, and the number of day traders is also small.

INSERT TABLE 2 ABOUT HERE

On average, the number of different securities traded per investor is roughly 0.2 at inception, and 0.3 at exit. Nevertheless, there is an investor that had traded 63 different securities before becoming at risk, and 104 when exiting the sample. With respect to mutual fund trading activity, the average number of funds' (buy) operations (funds' turnover) per investor is 2.8 (15,686 Euro) before entering the sample, and 6.1 (25,219 Euro) at exit.

4. Empirical findings

4.1. Disposition effect and literacy

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[5] A greater number of securities or funds in a portfolio is expected to be linked to more experience.

[6] In the construction of variables related to mutual funds trading activity we consider all mutual funds included in the investor's portfolio, including closed-end funds and open-end money funds, real estate funds and funds whose participants benefit from fiscal advantages.

A natural starting point for our investigation is to regress $SELL$ against TPI in a Cox proportional hazard model. Statistical inference is conducted using clustered robust standard errors at the investor-fund level (results are in the first row of Table 3).[7] The estimated hazard rate equals 1.72 and is statistically significant, meaning that the probability of a redemption is almost 72 percentage points higher when the investor is able to make a positive or null gross profit.

Beyond the average disposition effect, it is important to test whether this bias varies with the literacy of the investor. To that end, we first split our sample by bins of individuals and run the baseline specification for each separate group. We find a sizable (and statistically significant) difference between investors with and without a university degree. The estimated hazard rate for TPI equals 1.47 (1.91) in the subset of individuals with (without) higher education. The 44 percentage points difference is economically and statistically meaningful.[8]

INSERT TABLE 3 ABOUT HERE

The hazard rate for TPI is 1.45 for financially literate individuals and 1.88 for other individuals, a statistically significative difference at a 10% level. As to math skills, those with better abilities exhibit a smaller hazard rate for TPI than the others. The difference (44 percentage points) is statistically meaningful at a 1% level. We can therefore conclude that literacy is a pervasive moderator of the disposition effect displayed by mutual fund participants.

4.2. Disposition effect and trading experience

The effect of experience and learning is analyzed attending to the intensity of the trading activity, the sophistication of financial instruments held, and the diversity of the financial instruments traded. $Equitytrader$ and $bondtrader$ are two binary variables for which the value of one is assigned once an investor trades its first stock or bond, respectively, and zero otherwise. These variables are time-varying for they may change over the investment horizon of the investor.

[7] We report hazard rates rather than coefficients.

[8] The estimated hazard rate for TPI is 1.67 for the group of individuals with no information on education.

We first add $equitytrader$ to the baseline model along with its interaction with TPI (Table 4). Given that the coefficient for $equitytrader$ is not statistically significant, it may be inferred that, on average, equity traders and other investors have a similar investment horizon. More importantly, $equitytrader \times TPI$ is not statistically significant, meaning that equity traders and other investors exhibit, on average, a similar disposition effect. We obtain virtually identical results for $bondtrader$ and thus we conclude that the disposition effect is not affected by prior experience in stock or bond trading.

We replicate the previous exercise with three variables akin to securities trading initiation. The first is $derivativetrader$, a binary variable that is set to one in the wake of the first derivative trade, and zero otherwise. We add $derivativetrader$ and $TPI \times derivativetrader$ to the baseline specification, and re-run the estimation. In contrast with the former cases, $TPI \times derivativetrader$ loads negatively and its coefficient is statistically significant and economically sizable. This means that investors' experience in derivatives trading lowers loss aversion. Our interpretation of the results is that derivative trading requires a higher level of sophistication and knowledge than stock or bond trading; for that reason, we observe a partial reversion of the disposition effect.

The second and third variables – $foreigntrader$ and $daytrader$ - are equal to one once an investor starts trading a foreign security or engages in the first day trade, respectively. Neither of these covariates appear to affect the disposition effect: their interactions with TPI are not statistically significant.

INSERT TABLE 4 ABOUT HERE

The former variables capture different degrees of investor sophistication but fail to capture important features of the trading background, such as the intensity and the diversity of the trading activity. To get a sense as to whether trading intensity is materially relevant, we use the number of (buy) trades in securities markets.[9] To reduce the influence of outliers and skewness, a log transformation is applied: $lnnumtrades_t$ denotes the log of one plus the cumulative number of securities' buy trades performed up to t. We regress

[9] Trades in stocks, bonds and derivatives are considered.

$SELL$ against TPI and $TPI * lnnumtrades$.[10] The interaction term loads negatively with $SELL$, and it is economically and statistically significant.

Alternatively, we use value turnover as a measure of trading activity and compute the cumulative value turnover generated by investors' acquisitions in securities markets up to t; $lnturnover$ corresponds to the log of one plus the cumulative value turnover generated by investors' buys. Our estimates reveal that $lnturnover * TPI$ is statistically significant and loads negatively with the dependent variable. One important implication of these results is that trading experience reverses the disposition effect.

As regards trading diversity, interactions of TPI and the (log of the) number of different securities/funds traded by the investor are added to the baseline specification. The interaction of TPI and the (log of one plus the) number of different securities traded up to t ($lndiffsec_t$) is negative and statistically significant, and we observe a similar relationship when the interaction of TPI and the (log of the) number of different traded funds up to t ($lndifffunds_t$) is added to the baseline specification. In conjunction, these results tell us that trading diversity also reverses the disposition effect.

Two additional measures of investors' experience are considered: day trading intensity and the number of funds' trades. We add to the baseline specification the (log of one plus the) number of day trades performed by the investor up to t ($daytrading$) along with its interaction with TPI, and we do not find an association between these variables since $TPI * daytrading$ is statistically meaningless. Finally, the (log of the) number of funds' trades ($lnnumtradefunds$) is added, along with its interaction with TPI, and find that the coefficient for $TPI * lnnumtradefunds$ is negative and statistically significant. In other words, the higher the trading experience in terms of funds, the lower the reluctance to sell at loss.

To enrich our analysis, we re-estimate the earlier models while controlling for socio-demographic variables. The hazard ratio for *TPI* rises from 1.72 to 1.75. This small change could be either justified by the introduction of control covariates or by composition effects of the sample. In effect, the introduction of these additional variables lessens the number of observations available for the estimation, since the dataset contains missing values for some of the variables (namely occupation and education).

[10] In some of the regressions that involve continuous covariates, we exclude the covariate from the regression and concentrate on its interaction with TPI. The main reason is that the variable and its interaction with TPI present significant collinearity, thereby biasing the standard errors.

INSERT TABLE 5 ABOUT HERE

Columns [2] to [11] of Table 5 present alternative versions of the model, where $SELL$ is regressed against TPI, the set of socio-demographic variables, a variable denoting experience and its interaction with TPI. Our main interest continues to be the coefficient (hazard rate) of TPI and its interaction with variables representing experience. Hence, only the results for those variables are tabulated in the interest of conserving space. In essence, the introduction of control covariates only produces slight changes in the estimated coefficients, with the main conclusions of the analysis being preserved.

In auxiliary tests, we transform our continuous covariates into piecewise linear components. This approach offers two advantages: (i) hazard rates are easier to interpret; and (ii) it allows to further verify non-linear effects between dependent variables and regressors. The major disadvantage concerns the potential arbitrariness in the construction of these variables. Table 6 shows results for the estimation of piecewise linear specifications.

INSERT TABLE 6 ABOUT HERE

As regards trading diversity, $diffsec$ is converted into four different binary variables. $I(diffsec <= 3)_t, I(diffsec]3;6])_t, I(diffsec\,]6;10])_t$ and $I(diffsec > 10)_t$ are set to one when the investor displays no previous experience or invested in up to three different securities up to period t, traded between four and six different securities up to period t, traded between seven and ten different securities, or traded more than ten different securities up to period t, respectively. We regress *SELL* on these binary variables and their interactions with *TPI.* All interactions exhibit positive loads, with hazard ratios above one, although the sensitivity of the dependent variable to *TPI* drops with the number of different securities traded by investors (only $I(diffsec <= 3) * TPI$ and $I(diffsec]3;6]) * TPI$ are statistically significant). The probability of a sale more than doubles when the investor has low or no prior experience, vis-à-vis other investors.

A similar procedure is used with the number of trades: *SELL* is regressed on four piecewise binary variables and their interactions with *TPI*. Our results closely match those obtained for trading diversity and we observe greater disposition effect among investors with lower prior experience in securities markets. The hazard ratio for $I(numtrades >$

$20) * TPI$ is above one, but not statistically meaningful, suggesting that the disposition effect almost disappears when investors' trading intensity is high. Results are similar when piecewise linear components of turnover are considered instead as proxies for trading intensity (Table 6).

The effects of fund trading intensity and fund diversity are also re-examined using the piecewise linear framework. The coefficients for *I(numtradefunds <=5)*TPI*, *I((numtradefunds]5;10])*TPI* and *I(numtradefunds]10;30])*TPI* are positive and statistically significant. While the overall effect of the number of trades on the disposition effect is negative, the relationship is far from being linear. Indeed, the estimated hazard rate for *I(numtradefunds]5;10])*TPI* is greater than for *I(numtradefunds <=5)*TPI*, which contradicts the idea that the disposition effect correlates negatively with funds' trades. From that point forward, the hazard rate diminishes with the number of traded funds, and the disposition effect for individuals with between 11 and 30 trades is substantially weaker than for those with less than ten trades. Most significantly, individuals that performed more than 30 trades present no disposition effect. On the other hand, the disposition effect becomes weaker with fund diversity. Investors that acquired less than four different funds in the past exhibit a sharper disposition effect (hazard rate above 1.80). The hazard rate for investors that held more than six different funds drops to 1.27.

In aggregate, qualitative similar conclusions are attained when continuous variables and piecewise linear binary variables are employed in the assessment.

4.3. Disposition effect, trading experience and literacy

In this section we evaluate whether education, financial literacy and math skills affect the negative relationship between the disposition effect and the trading experience. Regression models are estimated separately using data on individuals holding a university degree and other individuals. We consider eleven alternative models, i.e., one model for each proxy for experience. The results are reported in Table 7, columns [1] and [2]. To conserve space, only hazard rates (and corresponding t-statistics) for the interaction of *TPI* and the experience variable are tabulated. Each line contains hazard rates for an alternative regression model.

INSERT TABLE 7 ABOUT HERE

The hazard rates associated to $TPI * equitytrader$, $TPI * bondtrader$, $TPI * derivativetrader$ and $TPI * foreigntrader$ are not statistically different from one in both subsets of individuals with and without university degree, meaning that past experience in trading stocks, bonds, derivatives and foreign securities do not impact the disposition effect of the two groups of individuals. However, experience with day trading reduces the disposition effect of less educated investors by 42 percentage points.

With respect to the number of trades and corresponding traded value, the coefficients for $TPI * lnnumtrades$ and $TPI * lnturnover$ are negative, statistically significant and almost identical in the two subsamples. A similar pattern is found for $TPI * lndiffsec$. Remarkably, $TPI * lnnumtradefunds$ and $TPI * lndifffunds$ have negative and statistically significant coefficients in the two subsets, but hazard rates are substantially lower for individuals with higher education. In other words, fund trading diversity and intensity produce higher impact on the disposition effect when individuals have a university degree.

In Table 7, columns [3] and [4], we tabulate results for a sample split based on knowledge about financial markets and products. The hazard rate for $TPI * equitytrader$ is above one and statistically significant for the group of individuals lacking financial literacy, and is also above one (although not statistically significant) for individuals with financial literacy, suggesting that stock trade onset exacerbates the disposition effect of less knowledgeable individuals. The hazard rates for $TPI * bondtrader$, $TPI * derivativetrader$ and $TPI * foreigntrader$ are not statistically different from one in both subsamples. However, day trade onset produces opposite effects on the two groups of individuals: those lacking financial literacy exhibit a weaker disposition effect in the wake of the first day trade and the disposition effect ramps up after the first day trade for the group of more knowledgeable individuals.

Interestingly, $TPI * lnnumtradefunds$ and $TPI * lndifffunds$ have negative and statistically significant coefficients in the two subsets but the overall impact of fund trading activity over the disposition effect is stronger for individuals with financial literacy. The coefficients for $TPI * lnnumtrades$ and $TPI * lnturnover$ are not statistically significant, but $TPI * lndiffsec$ is negative and statistically significant for less knowledgeable individuals.

Some of the results for the math skills' sample split closely mimic those obtained for financial literacy. For instance, the estimated hazard rate for $TPI * equitytrader$ is above one and statistically meaningful for the subset of individuals lacking math skills. As to individuals with higher math skills, the estimated hazard rate is below one, although not statistically significant. In the cases of $TPI * bondtrader$ and $TPI * derivativetrader$, the coefficients are not statistically significant.

On the other hand, the coefficient for $TPI * foreigntrader$ is negative (hazard rate below one) and statistically significant only for individuals with higher math skills, suggesting that trading experience with foreign securities lessens the disposition effect of investors with math skills, but not of other investors. The onset of day trading activity contributes (is not effective) to attenuate the disposition effect of individuals lacking (with) math skills, whilst the intensity of trading activity in securities markets (measured by $lnnumtrades$ and $lnturnover$) moderates the disposition effect of individuals with math skills, but not the disposition effect of other individuals.

The coefficient for $TPI * lndiffsec$ is negative and statistically significant for the two subsamples of individuals, but it is smaller for those that exhibit math skills. Put it in another way, securities markets experience, consubstantiated in trading intensity and diversity, seems to moderate the disposition effect, that effect being stronger for individuals with math skills. Also, the number of traded funds and fund diversity attenuate the disposition effect of all individuals. Puzzlingly, we find that while fund trading intensity produces stronger effects for individuals with math skills, the impact of fund diversity is stronger for individuals lacking those skills.

All in all, literacy plays a relevant role in shaping the way experience affects the disposition effect. Day trading activity weakens the disposition effect of less literate mutual fund investors (i.e., those with no university degree, those lacking financial literacy or math skills), but does not impact the disposition effect of the highly educated individuals. Concerning trading intensity in securities markets, the results are harder to interpret. Indeed, trading intensity produces virtually identical impact on the disposition effect of individuals with and without a university degree. However, when math skills are analyzed, trading intensity appears to produce lower effects for those that lack math skills. Finally, experience with mutual funds produces stronger effects for individuals with university education and financial literacy.

4.4. Additional robustness tests

The results presented thus far allow us to conclude that mutual fund investors exhibit disposition effect and that literacy and experience reverse, at least partially, this behavioral bias. In this section, we challenge these conclusions and consider alternative explanations for our empirical findings.

Our results could be explained by the existence of investors' irrational beliefs in mean reversion patterns of fund returns. We compute the 30- and the 180-day past returns up to t: *DRET30* (*DRET180*) takes the value of one if the fund generated positive returns in the past 30 (180) days and zero otherwise. These binary variables are introduced in separate empirical models, i.e., we add *DRET30* (*DRET180*) and its interaction with *TPI* to the baseline regression. If the reluctance to sell losers is entirely explained by mean reversion beliefs, then the *TPI* and *DRET30*TPI* coefficients should lack predictive power, whereas the coefficient for *DRET30* should be positive and significant. Accordingly, investors would sell funds with positive short-term returns irrespective of they being trading at a loss or at a gain.

The coefficient for *TPI* is positive and significant (0.258; hazard rate of 1.29), and the *DRET30* coefficient is negative.[11] Thus, if anything, the probability of a redemption declines with past performance. The coefficient of *TPI***DRET30* is positive and statistically significant, meaning that, on average, the probability of a redemption increases if the fund is trading at a gain (relative to the acquisition price) and has a positive short-term performance. Results for *DRET180* are very similar. Thus, the reluctance to sell losers cannot be solely explained by beliefs on return reversal. Even after controlling for this possibility, the reluctance to sell losers is preserved.

We also regress *SELL* on *TPI*, *DRET30* (or *DRET180*) and *TPI* times *DRET30* (or *DRET180*) separately for the sample of investors with university degree and for those without higher education. By and large, the point estimate for *TPI* remains substantially larger among those lacking a university degree, aligned with the idea that education attenuates the disposition effect. A similar procedure is used for experience, and the results of these auxiliary regressions confirm the role of trading experience (i.e., funds' trading intensity and diversity) as a moderator of the disposition effect.

An additional robustness test evaluates the impact of market sentiment on the disposition effect. We follow the methodology of Pagan and Sossounov (2003): the

[11] Non-tabulated results are available from the authors upon request.

sample is split into bull and bear market periods and the baseline model is estimated separately for each period. The point estimate for *TPI* in the bull/bear period is 0.83/0.28 (hazard rate of about 2.30/1.32), economically and statistically meaningful coefficients. Thus, mutual fund investors exhibit disposition effect in both periods, although they are more prone to sell past winners during bull periods.

To gauge whether sentiment also conditions the influence of literacy on the disposition effect, we conduct a numerical breakdown of our results by education level and conclude that the disposition effect rises during bull periods for individuals with and without a university degree. Nevertheless, that increase is remarkably stronger for investors lacking higher education. As for the impact of trading experience, our estimates confirm the role of experience as a moderator of the disposition effect during bull, but not bear, periods. In specific, investors with experience in stock trading and derivatives (especially those that day trade or invest in foreign securities) exhibit lower disposition effect during bull periods. Trading intensity and diversity of both securities and funds also alleviate the disposition effect during bull periods, and we do not find statistically significant results for these proxies when analyzing bear markets. To put it in another way, trading experience is particularly relevant as a moderator of the disposition effect during bull markets, but this effect ceases to exist during bear periods.

Next, we delve into the idea that investors look for someone to blame in the case of delegated investments (Chang, Solomon, and Westerfield 2016). To further examine this hypothesis, our sample of mutual funds is divided into those managed by subsidiaries of the financial institution where investors have their bank account, foreign mutual funds and other domestic mutual funds. We posit that the disposition effect should be stronger for other domestic mutual funds or foreign funds. The rationale behind this conjecture is that bank account managers are more likely to advice individuals to acquire mutual funds from their own financial institutions (or its affiliates) than other mutual funds. Correspondingly, if the effect of "look someone to blame" is relevant, it should be more expressive among those that actually followed the managers' advice, this meaning that the disposition effect should be weaker among these investors.

Our baseline model is estimated separately for each of the subsamples. The hazard rate for *TPI* is substantially larger when considering funds managed by the financial institution (1.92), than for those managed by other Portuguese financial institutions (1.26) or foreign institutions (1.23). These estimates do not conform to the notion that when fund participants have the opportunity to blame someone, they exhibit reverse disposition effect.

Another possible explanation for our findings is the existence of good and bad emotions. To alleviate concerns that our findings are driven by good/bad emotions, we introduce an additional variable in the baseline model: *emotions* is a binary variable indicating whether the last fund redeemed by the participant recorded a positive return as of the redemption date. If investors refrain from selling funds because the last time they redeemed at a loss, *emotions* should have a statistically significant and negative coefficient. The point estimate for *emotions* is positive and statistically significant, meaning that emotions influences investors' decision to redeem, but not in the way predicted by the theory. More importantly, however, the estimated hazard rate for *TPI* under this setting is 1.78, i.e., almost identical to the setting where emotions are not accounted for.

Finally, the presence of redemption fees in some funds could be the driving force of our results. We estimate the baseline regression for a sample of funds without subscription and redemption fees. The magnitude of the estimated hazard rate for *TPI* (1.21) drops substantially, but it is still statistically significant.

5. Conclusions

In this paper, we present an empirical analysis addressing the existence of disposition effect among mutual fund participants. To that end, a large sample of transaction-level records from a major Portuguese financial institution is assessed. Our dataset covers an extensive period from 1998 to 2017 and includes all trading records of 31,513 individuals. The disposition effect is evaluated through the lens of survival analysis, and our findings hint at a strong disposition effect among mutual fund investors: the probability of a fund redemption ramps up more than 70 percentage points when the mutual fund is trading at a gain. Our findings challenge the conclusions of Calvet, Campbell, and Sodini (2009a) and Ivković and Weisbenner (2009), who did not find evidence that mutual investors suffer from this bias.

In a second research question, we inquire whether financial literacy and trading experience weaken the disposition effect exhibited by mutual fund participants. Our results show that the tendency to hold losers is partially offset with literacy. In fact, we find that general literacy (i.e., holding a university degree) reduces the propensity to hold loser funds. In addition, higher financial knowledge and stronger math skills also reduce the reluctance to sell losers or the propensity to sell winners. On the other hand, trading sophisticated financial instruments such as derivatives appears to produce greater effects in moderating the disposition effect than trading traditional securities such as stocks or bonds.

We also find evidence consistent with the existence of irrational beliefs among mutual fund investors, but the disposition effect survives even after accounting for this bias. Likewise, we find that although the disposition effect is statistically and economically significant during both bull and bear markets, it is more sizable during periods of positive sentiment. In parallel, we gauge whether investors display lower disposition effect when there is someone to blame (as in the case of delegated investments) and reject this hypothesis. Finally, evidence of the disposition effect persists after accounting for bad emotions or redemption fees.

In sum, we present sound evidence that individual investors in mutual funds exhibit disposition effect and that this behavioral bias is partially offset with literacy. These findings have relevant normative implications given that the existence of the disposition effect imposes substantial costs on investors: there are benefits for investors (and the society) from the acquisition of higher levels of literacy.

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Table 1 – Variable definition

Panel A – Socio-demographic variables/ static variables

gender	A binary variable set to one (zero) if the investor is a male (female).
age	The age of the investor at the transaction date.
educ0	A binary variable set to one if the investor does not have secondary education, and zero otherwise.
educ1	A binary variable set to one if the investor does have secondary education, but does not hold a university degree, and zero otherwise.
Educ2	A binary variable set to one if the investor does have a university degree, and zero otherwise.
ocup0	A binary variable set to one if the investor is an undifferentiated worker, and zero otherwise.
ocup1	A binary variable set to one if the investor is an unqualified specialized worker and zero otherwise.
ocup2	A binary variable set to one if the investor is a qualified worker (without management responsibilities) and zero otherwise.
ocup3	A binary variable set to one if the investor is a director and zero otherwise.
savings account	A binary variable set to one if the investor has a savings account and zero otherwise.
mortgage	A binary variable set to one if the investor has a mortgage and zero otherwise.
consumer credit	A binary variable set to one if the investor has a consumer credit and zero otherwise.
finlit	A binary variable set to one if the investor has an occupation related to the financial system or a job in the areas of accounting and finance, and zero otherwise.
mathskills	A binary variable set to one if the investor has an occupation that requires advanced math skills, and zero otherwise.
lispor	A binary variable set to one if the investor lives in Lisbon or Oporto, and zero otherwise.

Panel B – Experience related-variables/dynamic variables

equitytrader	A binary variable that takes the value of one after the first stock trade of the investor, and zero otherwise.
bondtrader	A binary variable set to one after the first bond trade of the investor, and zero otherwise.
derivativetrader	A binary variable set to one after the first derivative trade of the investor, and zero otherwise.
foreigntrader	A binary variable set to one after the first trade of a foreign security, and zero otherwise.
daytrader	A binary variable set to one after the first stock day trade of the investor, and zero otherwise.
numtrades	cumulative number of buy trades performed in securities markets. This variable considers trades in different securities, namely stocks, bonds and derivatives.
turnover	cumulative trading volume generated by the buy trades performed in securities markets. This variable considers trades in different securities, namely stocks, bonds and derivatives.
daytrading	cumulative number of day trades performed in securities markets. A day trade event takes place when the investor buys and sells a security in the same trading session.
diffsec	number of different securities traded/held by the investor
difffunds	number of different funds traded/held by the investor (includes all types of funds including all closed-end funds and open-ended money market funds, real estate funds, and funds associated to fiscal benefits)
numtradefunds	cumulative number of funds' buy trades.
I(*diffsec* <=3)	binary variable set to one when the investor displays no previous experience or invested in up to three different securities up to period t.
I(*diffsec*]3;6])	binary variable equal to one if the investor traded between four and six different securities up to period t
I(*diffsec*]6;10])	binary variable equal to one if the investor traded between seven and ten different securities up to period t
I(*diffsec* >10)	binary variable that assumes the value of one if the investor traded more than 10 different securities up to period t.
I(*numtrades* <=5)	binary variable set to one when the investor carried out five or less (buy) operations in securities markets up to period t.
I((*numtrades*]5;10])	binary variable set to one if the investor performed between six and 10 buy operations in securities markets up to period t.
I(*numtrades*]10;20])	binary variable set to one if the investor performed between 11 and 20 buy operations in securities markets up to period t.
I(numtrades >20)	binary variable that assumes the value of one if the investor performed more than 20 buy operations up to period t, and zero otherwise.
I(*turnover* <=10)	set to one when investors have no prior experience in securities markets or had traded less than 10,000 Euro up to period t, and zero otherwise.
I(turnover]10;100])	takes the value of one when investors had traded between 10,000 and 100,000 Euro up to period t, and zero otherwise.
I(*turnover* >100])	takes the value of one when investors had traded more than 100,000 Euro up to period t, and zero otherwise.

I(numtradefunds <=5)	set to one if the investor traded fund shares five times or less up to period t, and zero otherwise
I((numtradefunds]5;10])	assumes the value of one if the investor carried out between six to ten fund transactions up to period t, and zero otherwise
I(numtradefunds]10;30])	takes the value of one if the investor carried out between eleven and 30 fund transactions up to period t, and zero otherwise
I(numtradefunds >30)	one if the investor undertook more than 30 fund transactions up to period t, and zero otherwise
I(difffunds <=3)	one when the investors had subscribed between one and three different funds up to period t
I(difffunds]3;6])	one when the investors had subscribed between four and six different funds up to period t
I(difffunds >6)	is set to one after investor had subscribed more than six different funds up to period t.

Table 2 – Descriptive statistics

The table presents summary statistics of the data used in the assessment. Our sample contains 31,513 different investors. Panel A portraits the sample regarding the socio-demographic characteristics of investors. Panel B describes the sample with respect to investors' trading background before becoming at risk (i.e., before acquiring mutual funds' shares) and when they exit the sample (i.e., when they redeem all mutual funds' shares or at February 2017, whichever arrives first).

Panel A – Socio-demographic variables

	(% of investors)
Region	
Lisbon or Oporto	37.5
Other	62.5
Education	
Missing	32.0
Less than 12 years education	40.7
Secondary Education	13.6
University	13.8
Savings account	
Yes	27.7
No	72.3
Consumer Credit	
Yes	3.3
No	96.7
Mortgage	
Yes	7.0
No	93.0
Gender	
Female	38.5
Male	61.5
Financial Literacy	
Missing	30.4
Yes	3.8
No	65.8
Math Skills	
Missing	30.5
Yes	5.2
No	64.3
Occupation	
Missing	30.4
Non-employed	13.2
Undifferentiated	5.1
Specialized	35.7
Qualified	7.6
Manager	8.0

Panel B – Trading background

		Mean	Std. Deviation	Minimum	Maximum	Percentiles		
						25	50	75
equitytrader	At inception	4.0%	19.7%	0.0%	100.0%	0.0%	0.0%	0.0%
	At exit	8.0%	26.8%	0.0%	100.0%	0.0%	0.0%	0.0%
bondtrader	At inception	1.0%	8.4%	0.0%	100.0%	0.0%	0.0%	0.0%
	At exit	2.0%	13.5%	0.0%	100.0%	0.0%	0.0%	0.0%
# daytrades	At inception	0.01	0.42	0	51	0	0	0
	At exit	0.03	1.15	0	140	0	0	0
# of buy trades	At inception	0.42	5.62	0	704	0	0	0
	At exit	1.03	10.27	0	1072	0	0	0
Turnover of buy trades (Euro)	At inception	2217	43624	0	4000000	0	0	0
	At exit	5195	79880	0	6413403	0	0	0
# of different securities	At inception	0.2	1.0	0.0	63.0	0.0	0.0	0.0
	At exit	0.3	1.6	0.0	104.5	0.0	0.0	0.0
# of buy operations (funds)	At inception	2.8	10.3	1.0	212.0	1.0	1.0	2.0
	At exit	6.1	20.0	1.0	1236.0	1.0	2.0	4.0
Fund subscriptions (in Euro)	At inception	15686	64451	0	6519263	1895	4988	12470
	At exit	25219	92114	0	7219767	2958	7491	20376
# of different funds	At inception	1.4	1.1	1.0	33.0	1.0	1.0	1.5
	At exit	2.1	3.3	1.0	139.0	1.0	1.0	2.0

Table 3 – Disposition effect and investors' characteristics

The table below presents hazard ratios associated with mutual fund participants' decision to hold/redeem fund shares. The dependent variable assumes the value of one every week the mutual fund participant redeems fund shares and zero when he/she holds the fund shares. The dependent variable is regressed against *TPI* (binary variable set to one when the fund price is equal or above the purchase average weighted price, and zero otherwise). The model is estimated for the full sample and for different subsamples: (i1) investors with financial literacy; (i2) investors with no financial literacy; (ii1) investors with math skills; (ii2) investors with no math skills; (iii1) investors with a university degree; and (iii2) investors without a university degree. Our dataset is comprised between January 1998 and February 2017. T-statistics are clustered at the investor-fund level. ***, **, * denote two-side statistical significance at the 1%, 5% and 10% level.

	Coef.	t-stat	Groups display equal coef. (t-stat)
Full Sample	1.72***	(29.43)	
No Fin. Literacy	1.88***	(25.29)	
Fin. Literacy	1.45***	(3.34)	-1.79*
No Math. Literacy	1.88***	(25.06)	
Math. Literacy	1.44***	(4.25)	-2.40***
No University Degree	1.91***	(25.04)	
University Degree	1.47***	(9.45)	-5.40***

Table 4 – Disposition effect, sophistication and trading experience

The table below presents hazard ratios associated with mutual fund participants' decision to hold/redeem fund shares. The dependent variable assumes the value of one every week the mutual fund participant redeems fund shares and zero when he/she holds the fund shares. *TPI* is a binary variable set to one when the fund price is equal or above the purchase average weighted price, and zero otherwise. *TPI* is interacted with different variables in a multi-regression setup: *equitytrader, bondtrader, derivativetrader, foreigntrader, daytrader, lnnumtrades, lnnumtradefunds, lnturnover, daytrading, lndiffsec* and *lndifffunds*. The estimation is conducted via Cox proportion hazard model. Our dataset is comprised between January 1998 and February 2017. T-statistics are clustered at the investor-fund level. ***, **, * denote two-side statistical significance at the 1%, 5% and 10% level.

	[1]	[2]	[3]	[4]	[5]	[6]
TPI	1.72***	1.72***	1.72***	1.72***	1.73***	1.73***
	(29.43)	(27.86)	(29.11)	(28.77)	(29.37)	(29.49)
equitytrader		1.01				
		(0.26)				
*TPI*equitytrader*		1.07				
		(1.03)				
bondtrader			0.61***			
			(-3.58)			
*TPI*bondtrader*			1.02			
			(0.10)			
derivativetrader				0.70***		
				(-3.58)		
*TPI*derivativetrader*				0.80**		
				(-2.02)		
foreigntrader					1.37***	
					(2.75)	
*TPI*foreigntrader*					0.91	
					(-0.68)	
daytrader						1.87***
						(4.00)
*TPI*daytrader*						0.87
						(-0.85)
N	6926515	6926515	6926515	6926515	6926515	6926515
Log-lik	-509222.3	-509214.6	-509173.0	-509107.8	-509211.7	-509198.2
id-funds	36406	36406	36406	36406	36406	36406
Chi2	866.2***	878.1***	902.8***	941.8***	877.7***	902.7***
Pseudo-R2	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%
Control Variables	No	No	No	No	No	No
Clustered SE	ID-fund	ID-fund	ID-fund	ID-fund	ID-fund	ID-fund

	[1]	[2]	[3]	[4]	[5]	[6]
TPI	2.14***	1.73***	1.73***	1.73***	1.73***	2.43***
	(20.11)	(29.24)	(29.28)	(29.46)	(29.43)	(20.10)
lnnumtradefunds	1.19***					
	(8.45)					
*TPI*lnnumtradefunds*	0.88***					
	(-6.42)					
lnnumtrades						
*TPI*lnnumtrades*		0.97*				
		(-1.70)				
lnturnover						
*TPI*lnturnover*			0.99***			
			(-2.39)			
daytrading				1.35***		
				(3.17)		
*TPI*daytrading*				0.99		
				(-0.11)		
lndiffsec						
*TPI*lndiffsec*					0.93***	
					(-3.00)	
lndifffunds						1.19***
						(6.10)
*TPI*lndifffunds*						0.73***
						(-9.09)
N	6926515	6926515	6926515	6926515	6926515	6926515
Log-lik	-509113.2	-509218.4	-509214.3	-509205.2	-509210.3	-509124.6
id-funds	36406	36406	36406	36406	36406	36406
Chi2	954.2***	866.4***	866.8***	902.0***	868.7***	910.1***
Pseudo-R2	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%
Control Variables	No	No	No	No	No	No
Clustered SE	ID-fund	ID-fund	ID-fund	ID-fund	ID-fund	ID-fund

Table 5 – Disposition effect, sophistication and trading experience: controlling for socio-demographic characteristics

The table below presents hazard ratios associated with mutual fund participants' decision to hold/redeem fund shares. The dependent variable assumes the value of one every week the mutual fund participant redeems fund shares and zero when he/she holds the fund shares. *TPI* is a binary variable set to one when the fund price is equal or above the purchase average weighted price, and zero otherwise. *TPI* is interacted with different variables in a multi-regression setup: *equitytrader, bondtrader, derivativetrader, foreigntrader, daytrader, lnnumtrades, lnnumtradefunds, lnturnover, daytrading, lndiffsec* and *lndifffunds*. Sociodemographic variables are used as control variables. The estimation is conducted via Cox proportion hazard model. Our dataset is comprised between January 1998 and February 2017. T-statistics are clustered at the investor-fund level. ***, **, * denote two-side statistical significance at the 1%, 5% and 10% level.

	[1]	[2]	[3]	[4]	[5]	[6]
TPI	1.75***	1.74***	1.75***	1.76***	1.76***	1.76***
	(26.50)	(24.39)	(26.27)	(26.12)	(26.34)	(26.51)
equitytrader		0.92				
		(-1.55)				
*TPI*equitytrader*		1.07				
		(1.05)				
bondtrader			0.61***			
			(-3.18)			
*TPI*bondtrader*			1.00			
			(-0.01)			
derivativetrader				0.74***		
				(-2.66)		
*TPI*derivativetrader*				0.78*		
				(-1.89)		
foreigntrader					1.24*	
					(1.75)	
*TPI*foreigntrader*					0.93	
					(-0.49)	
daytrader						1.74***
						(3.38)
*TPI*daytrader*						0.85
						(-0.94)
N	4710630	4710630	4710630	4710630	4710630	4710630
Log-lik	-362046.3	-362044.0	-362006.6	-361968.8	-362042.1	-362030.1
N. id-funds	25447	25447	25447	25447	25447	25447
Chi2	1467.6***	1472.8***	1505.3***	1506.6***	1477.0***	1491.5***
Pseudo-R2	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	ID-fund	ID-fund	ID-fund	ID-fund	ID-fund	ID-fund

	[7]	[8]	[9]	[10]	[11]	[12]
TPI	2.27***	1.77***	1.78***	1.76***	1.78***	2.55***
	(18.90)	(26.40)	(26.48)	(26.49)	(26.63)	(18.44)
lnnumtradefunds	1.20***					
	(8.16)					
*TPI*lnnumtradefunds*	0.86***					
	(-6.83)					
lnnumtrades						
*TPI*lnnumtrades*		0.95***				
		(-2.76)				
lnturnover						
*TPI*lnturnover*			0.99***			
			(-3.49)			
daytrading				1.26***		
				(1.97)		
*TPI*daytrading*				0.99		
				(-0.14)		
lndiffsec						
*TPI*lndiffsec*					0.89***	
					(-3.78)	
lndifffunds						1.22***
						(5.99)
*TPI*lndifffunds*						0.72***
						(-8.47)
N	4710630	4710630	4710630	4710630	4710630	4710630
Log-lik	-361957.0	-362035.1	-362028.1	-362036.1	-362025.6	-361968.0
N. id-funds	25447	25447	25447	25447	25447	25447
Chi2	1493.4***	1474.8***	1481.0***	1483.3***	1483.0***	1516.9***
Pseudo-R2	0.5%	0.5%	0.5%	0.5%	0.5%	0.5%
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	ID-fund	ID-fund	ID-fund	ID-fund	ID-fund	ID-fund

Table 6 – Disposition effect and trading experience: a piecewise linear components' approach

The table below presents hazard ratios associated with mutual fund participants' decision to hold/redeem fund shares. The dependent variable assumes the value of one every week the mutual fund participant redeems fund shares and zero when he/she holds the fund shares. The dependent variable is regressed against *TPI* (binary variable set to one when the fund price is equal or above the purchase average weighted price, and zero otherwise), variables representing investors' experience and interactions of investors' experience with *TPI*. Piecewise linear components of continuous variables (*numtrades*, *numtradefunds*, *turnover*, *diffsec* and *difffunds*) representing trading experience are utilized as covariates in the econometric specification. The estimation is conducted via Cox proportion hazard model. Our dataset is comprised between January 1998 and February 2017. T-statistics are clustered at the investor-fund level. ***, **, * denote two-side statistical significance at the 0.1%, 1% and 5% level.

	[1]	[2]	[3]	[4]	[5]
I(*diffsec* <=3)*TPI	1.69*** (26.58)				
I(*diffsec*]3;6])*TPI	1.19*** (3.15)				
I(*diffsec*]6;10])*TPI	1.10 (0.52)				
I(*diffsec* >10)*TPI	1.19 (0.67)				
I(*numtrades* <=5))*TPI		1.74*** (29.19)			
I((*numtrades*]5;10])*TPI		1.80*** (4.48)			
I(*numtrades*]10;20])*TPI		1.33* (1.87)			
I(*numtrades* >20)*TPI		1.18 (0.91)			
I(*turnover* <=10)*TPI			1.88*** (10.42)		
I(*turnover*]10;100])*TPI			1.62*** (4.90)		
I(*turnover* >100])*TPI			1.27 (1.50)		
I(*difffunds* <=3)*TPI				1.84*** (29.74)	
I(*difffunds*]3;6])*TPI				1.41*** (5.65)	
I(*difffunds* >6)*TPI				1.27*** (4.33)	
I(numtradefunds <=5)*TPI					1.80*** (25.95)
I((numtradefunds]5;10])*TPI					2.06*** (17.08)
I(numtradefunds]10;30])*TPI					1.65*** (9.91)
I(numtradefunds >30)*TPI					0.95 (-0.76)

Table 7 – Subsample analysis: financial literacy, math skills and education

The table below presents hazard ratios associated with mutual fund participants' decision to hold/redeem fund shares. The dependent variable assumes the value of one every week the mutual fund participant redeems fund shares and zero when he/she holds the fund shares. The dependent variable is regressed against *TPI* (binary variable set to one when the fund price is equal or above the purchase average weighted price, and zero otherwise), a variable capturing trading experience (*derivativetrader, lnnumtrades, lnturnover, lndiffsec* and *lndifffunds*) and an interaction of *TPI* with the former. The estimation is conducted via Cox proportion hazard model. Our dataset is comprised between January 1998 and February 2017 and is collapsed by (i) financial literacy, math skills and education (university degree). To save space, only the hazard ratios and t-statistics for the interaction of *TPI* and the variable capturing trading experience are tabulated. T-statistics are clustered at the investor-fund level. ***, **, * denote two-side statistical significance at the 1%, 5% and 10% level.

	Subsample					
	No University	University	No Math Skills	Math Skills	No Financial Lit.	Financial Lit.
Interaction of TPI with						
equitytrader	1.11 (1.22)	0.99 (-0.13)	1.18* (1.82)	0.94 (-0.33)	1.16* (1.68)	1.15 (0.55)
bondtrader	1.01 (0.06)	1.08 (0.34)	1.03 (0.11)	0.91 (-0.22)	1.02 (0.09)	1.09 (0.17)
derivativetrader	0.89 (-0.70)	0.79 (-1.35)	0.85 (-0.90)	0.66 (-1.33)	0.84 (-0.99)	1.17 (0.33)
foreigntrader	1.25 (0.66)	0.81 (-1.09)	1.16 (0.67)	0.47*** (-2.36)	1.14 (0.62)	0.63 (-1.15)
daytrader	0.58* (-1.90)	1.38 (1.18)	0.59*** (-2.30)	1.58 (0.77)	0.60*** (-2.31)	3.14* (1.70)
lnnumtradefunds	0.90*** (-3.31)	0.81*** (-5.79)	0.90*** (-3.34)	0.75*** (-3.92)	0.90*** (-3.44)	0.74*** (-2.93)
lnnumtrades	0.92*** (-3.39)	0.93*** (-2.68)	0.97 (-0.97)	0.86* (-1.79)	0.97 (-1.13)	1.03 (0.52)
lnturnover	0.98*** (-3.75)	0.98*** (-3.45)	0.99 (-1.36)	0.98* (-1.66)	0.99 (-1.52)	1.00 (-0.09)
daytrading	0.88 (-0.83)	1.14 (0.98)	0.80* (-1.82)	1.17 (0.47)	0.83* (-1.73)	1.71*** (2.05)
lndiffsec	0.86*** (-3.81)	0.86*** (-3.54)	0.93* (-1.76)	0.87*** (-1.99)	0.92* (-1.94)	1.00 (0.02)
lndifffunds	0.85*** (-2.29)	0.74*** (-5.68)	0.67*** (-4.09)	0.75*** (-4.94)	0.75*** (-5.05)	0.68*** (-2.78)