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Behavioural Biases Among Retail and Institutional Investors

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Abstract

Decision-makers are often subject to various behavioural biases. Although they may affect both retail investors and professional money managers, behavioural biases are likely to be more severe among retail investors. The objective of this short note is to present an overview of the main biases that have been detected and to describe how one can empirically identify and measure them. We start by introducing two broad types of behavioural biases: those affecting beliefs and those affecting preferences. Then we discuss some of the most popular biases that can be traced among investment decisions: (1) excessive trading, i.e., investors trading more than what can be justified by rational choice, (2) disposition effect, i.e., the tendency to sell winning stocks and hold losing ones and (3) home bias, i.e., investors' portfolio tilt towards domestic equities

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1 An Overview on Behavioral Biases

Behavioral biases can be categorized into *biases in beliefs* and *biases in preference* (Barberis and Thaler (2003), Barberis (2018)). *Biases in beliefs* relate to how individuals estimate the probability of an event, based on prior knowledge of conditions that might be related to the event. In practice, individuals are often updating their belief in violation of Bayes' rule. [1] The second type, *biases in preferences*, is related to how people assess risky gambles, given their beliefs, in a way that violates the traditional expected utility theory.[2]. While lab experiments are useful to detect cognitive biases, there is some evidence in the field suggesting the presence of such biases in investors' decisions.

1.1 Biases in Beliefs

Tversky and Kahneman (1974) were among the first to observe different pathologies in people's probability assessments. For example, individuals tend to ignore prior probabilities, they sometimes infer patterns from a series of random unrelated events, or ignore the precision (for example or the small sample size) of evidence that is used to assess probability, etc. The *representativeness heuristic* is an important bias related to the tendency to judge likelihoods based on naïve comparisons of characteristics of the event being predicted with characteristics of the observed sample. This bias is difficult to observe by simply looking at individuals' trading decisions. Evidence of this bias is first documented in lab experiments (Kahneman and Tversky (1972, 1973)) where subjects are directly asked to assess the probability of an event given some information[3]. Researchers can also look at investors' reactions around some specific events whose probabilities are likely to be misjudged given the context. For example, Cooper et al. (2001, 2005b) explore how investors react to name-changing events of companies during and after the dot-com bubble in the late

[1]Bayes' rule calculates the conditional probability of an event, based on the values of specific related known probabilities. It states that the conditional probability of an event, based on the occurrence of another event, is equal to the likelihood of the second event given the first event multiplied by the probability of the first event.

[2]Expected utility theory states that decision makers choose between risky or uncertain prospects by comparing their expected utility values, i.e., the weighted sums obtained by adding the utility values of the outcomes multiplied by their respective probabilities. Agents have a utility function that is increasing, concave, and defined over consumption outcome and they make the decision to maximize their expected utility.

[3]An example of the question: Mary is quiet, studious, and concerned with social issues. While an undergraduate at Berkeley, she majored in English literature and environmental studies. Given this information, indicate which of the following three cases is most probable: A. Mary is a librarian; B. Mary is a librarian and a member of the Sierra Club; C. Mary works in the banking industry. More than half of the participants choose B as the description matches the personal trait of someone who is a librarian and a member of the Sierra Club the most (Nofsinger (2017)

1990s. They show that companies that change their names to dot-com during the bubble and those removing dot-com from their names after the bubble earned significantly positive abnormal returns (whether or not the companies are related to the internet). This can be explained by investors' eagerness to be associated with an internet company during the bubble (and the reverse after the bubble), which led them to form a biased belief on the true value of internet-unrelated companies. In the same vein, Cooper et al. (2005a) document a significant increase in flows (after controlling for funds' performance) when a fund changes its name towards the current high-return style and/or away from the current low-return style. As in the above example, the increase in fund flows is regardless of whether the new name matches the fund's style. This suggests some mutual fund investors naïvely update their belief about funds' future performance based on fund names.

Another mistake in subjective probabilities judgment is the *extrapolative bias*. It is the tendency to form expectations of returns (or fundamentals) as a positive function of past realizations. Evidence of this bias usually comes from surveys where researchers directly ask respondents about their expectations on various economic variables. For example, Amromin and Sharpe (2014) and Greenwood and Shleifer (2014) document extrapolative bias in investors' stock returns' expectation elicited from various large-scale surveys. Da et al. (2021), using data from a crowdsourcing platform for ranking stocks, show that investors extrapolate from recent past returns, with more weight on the more recent observations. Kuchler and Zafar (2019) show that individuals' experience of recent changes in local house prices has a positive impact on their expectation of US house prices in the following year. Extrapolative expectations are also detected in controlled experiments where participants are asked to state their forecasts about economic variables when past realizations are available to them (see for example Afrouzi et al. (2021), Andries et al. (2020), Beutel and Weber (2022)). Some empirical evidence on investors' trading may also suggest extrapolative bias. Sirri and Tufano (1998) document that mutual fund investors invest more in funds that did very well in the previous period, suggesting that they may have naively extrapolated on past returns, while there is a lack of empirical evidence for such persistence in performance (Grinblatt et al. (1995); Carhart (1997)).

Overconfidence is another bias in beliefs having large consequences on investors' portfolio decisions. Evidence for overconfidence can be detected in surveys or experiments where participants are asked to judge their ability or the precision of their belief. For example, when being asked to rate their ability against others, 94% of university professors in the sample considered their teaching ability to be better than average (Cross (1977)). 88% of American college students and 77% of Swedish ones rate themselves above the 50th percentile in driving safely (Svenson (1981)). In an experiment, when being asked to give a 90% confidence interval for their numerical answers to a question (for example, how old is Madonna?), the intervals given by participants contain the true answers only 43% of the time, suggesting overconfidence in their estimation (Klayman et al. (1999))[4].

Other biases related to investors' beliefs include *belief perseverance*, i.e., people's propensity to "attach" too much to their belief, and for too long, failing to use new evidence to update it (Lord et al. (1979)); *anchoring*, i.e., people's tendency to start from an arbitrary value when forming an estimation, and make insufficient adjustment around it (Tversky and Kahneman (1974)); *availability bias*, i.e., people's tendency to be influenced by the more recent and salient occurrence of an event when estimating its likelihood (Tversky and Kahneman (1974)).

1.2 Biases in Preferences

People must often take decisions under uncertainty. The Expected Utility theory states that people should estimate the likely utility of their actions and choose the action with the highest expected (ie probability weighted) utility. However, this theory seems largely violated in practice. Tversky and Kahneman (1992), Kahneman and Tversky (2013) proposed to explain the observed deviations by a new behavioral model, the *prospect theory*, where people think in terms of expected utility relative to a reference point (e.g. current wealth) rather than absolute outcomes. In this model, the decision maker is also (1) loss averse, in the sense that the disutility of a loss is greater than the utility brought by a gain of the same size, and (2) risk-averse on the gain domain (preferring the certain outcome with a lower expected utility to the risky outcome) but risk-seeking on the loss domain (preferring the outcome that has a lower expected utility but the potential to avoid losses). Finally, the probability weighting function overweights low-probability outcomes and underweights high-probability ones.

Another frequently observed bias is that loss-averse investors take too short-term view of their investments, leading them to react overly negatively to short-term losses, at the expense of long term benefits. In practice, the more investors evaluate their portfolios, the higher their chance of seeing a loss and, thus, the more susceptible they are to loss aversion. Benartzi and Thaler (1995) introduce the concept of *Myopic loss aversion* (MLA), a combination of a greater sensitivity to losses than to gains and a tendency to evaluate outcomes frequently.[5] This bias results in households' reduced risk participation as it makes risky assets less attractive to investors. It is particularly wealth-destroying for long-term investors such as those investing in retirement plans. Many lab experiments show that the way the investment opportunities are presented has a large impact on investors' risk participation (see Benartzi and Thaler (1995), Thaler et al. (1997), Gneezy and Potters (1997) and Haigh and List (2005) for example). In particular, when investors are induced to evaluate their invest-

[4]For a thorough survey on overconfidence bias, see Moore and Healy (2008) and Alicke and Govorun (2005).

[5]The first component of MLA is *narrow framing*, i.e., the tendency to treat each financial outcome in the separation of each other and of the total wealth. The second one is *loss aversion*, also an important component of the prospect theory.

ment over a longer horizon to avoid experiencing losses in short intervals, they invest a significantly larger proportion of their wealth in risky assets. Shaton (2017) shows that, following a regulatory change in the frequency at which retirement fund performance is displayed (from 1-month to 12-month horizon), flows into riskier funds increase significantly compared to the control group.

The *status-quo bias* (SQB) (also known as *inaction* or *inertia*) is another bias that can be explained by loss aversion: people focus more on what they stand to lose from a decision than what they stand to gain. An individual suffering from the status-quo bias chooses alternatives that have been chosen before even if these alternatives are no longer optimal. SQB is often detected in lab experiments (see, for example, Kahneman et al. (1991) and Samuelson and Zeckhauser (1988)). Outside the lab, a number of studies have shown a lack of active change in individual investor's decisions. For example, Ameriks and Zeldes (2004) documents that 73 percent of participants in the largest pension provider in the US make no change to their asset allocation during ten years. Agnew et al. (2003) show that 401K participants in a large firm tend to remain with the default option. Specifically, having entered the plan before 1994, when the default choice is 100% in a risk-free fund, reduces participants' allocations to equity funds by 31.92%. Calvet et al. (2009) shows that investment inertia tends to decrease with households' financial wealth, education and size. It can also be reduced with robo-advice (Bianchi and Brière (2021)).

Another common bias in preferences is *ambiguity aversion*, i.e. the preference for known risks over unknown risks. People generally dislike situations with a large uncertainty on the probability distribution of an event (Ellsberg (1961)). Evidence on ambiguity aversion are often experimentally documented (for example, see Becker and Brownson (1964), Heath and Tversky (1991), Fox and Tversky (1995)). Barberis (2018) mentions ambiguity aversion as an explanation for the home and local bias (covered in the section that follows). For example, Benartzi (2001) documents that employees allocate 10.37% to 39.70% of their retirement savings on their own company stocks. Coval and Moskowitz (1999) find that fund managers have a preference for companies with headquarters closer to them.

2 Testable Biases in Investors' Trading

A large number of the cognitive biases in investors' beliefs or preferences discussed in the previous section can only be detected by running experiments in the lab. But some of these cognitive biases can also have testable consequences on investors' trading activity. In the subsections that follow, we discuss how to identify and measure from trading data three important behavioral biases: excessive trading, disposition effect and home bias. We also discuss the empirical evidence of these biases among retail and institutional investors.

2.1 Excessive Trading

We refer to excessive trading when investors trade more than what can be justified by rationality. Investors may trade too much if the additional profit brought by trading activities in a period is not sufficient to offset the transaction costs born during the same period.

Under a rational expectation framework (Grossman and Stiglitz (1980)), investors should trade when the marginal benefit of trading is equal to or exceeds the marginal cost of the trade. But if investors are overconfident (see, for example, Barberis and Thaler (2003), Odean (1999), Barber and Odean (2001)), they may overestimate the precision of their signals and hence expect profits from trades to be higher than the rationally expected ones, which drives them to take inefficient trading actions. As shown in Odean (1999), Barber and Odean (2002), Grinblatt and Keloharju (2000), Choi et al. (2002) and Barber et al. (2009) for example, excessive trading is often associated with poor portfolio return net of transaction cost.

2.1.1 A simple measure of excessive trading

In his seminal paper on the topic, Odean (1999) proposes a simple measure for excessive trading. The idea is to look at whether the securities investors buy outperform the ones they sell, taking into account estimates for the transaction costs of the trades. He thus measures the difference between the average return on all the securities bought and the one on all the securities sold and compares this difference to the round-trip transaction cost. Consider a time period of T days, indexed by $= 1, 2, ..., T$ and N purchases, indexed by i, $i = 1, 2, ..., N$. Each transaction includes a security j_i and a trading date t_i. The average return to the bought securities subsequent to their purchase over T tradings days is computed as:

$$R^B_{T,P} = \frac{\sum_{i=1}^{N} \Pi_{\tau=1}^{T}(1 + R_{ji,t_{i+\tau}})}{N} - 1 \tag{1}$$

where $R_{j,t}$ is the daily returns on security j on date t_i.

Similarly, one can compute $R^S_{T,P}$, the average return on all the sold securities subsequent to their sale during period T. The difference between the two can be compared against the estimated transaction costs.

Odean (1999) uses daily trades data on NYSE, American Stock Exchange (ASE), and NASDAQ of ten thousand customers of a nationwide discount brokerage house. In this study, the author estimate the average round-trip transaction cost to be 5.9 percent. Their statistical tests suggest that the returns from trades are negative with and without consideration of transaction costs[6].

[6] Testing that the return difference between the bought and sold securities is significantly larger than the transaction cost requires an adequate statistical test. The procedure faces a big challenge of independence between returns from different trades. In particular, the same securities can be bought or sold on more than one day or be bought or sold on the same day by different accounts. This dependence between trading observations may invalidate statistical

Barber et al. (2009) use a similar approach on Taiwanese stock market data and show that stocks sold by individual investors outperform the ones they bought with and without taking into account the transaction costs. Losses from individual investors' trading activities can be traced back to gross trading loss, inefficient market timing, commission, and transaction taxes.

2.1.2 "Own-benchmark" abnormal returns measure

Odean (1999) measure simply compares the gross performance of the portfolio to trading costs. Later, excessive trading measures have been developed by Barber and Odean (2000), Barber and Odean (2002) and Barber and Odean (2001) to compare the performance of ones' portfolios and a so-called "own-benchmark portfolio". This is the return an investor would have earned had he held his beginning-of-year portfolio for the entire year (i.e., assuming no buying/selling from the beginning of period T). The idea is that if an investor obtains a return net of transaction costs that is lower than what he could have earned without further trading activities, this is a sign of excessive trading. Note that additionally, to account for investor's heterogeneous style exposures and measure investors' skills, Barber and Odean (2000) also calculate portfolio's alpha relative to the market or to Fama-French factors.

2.1.3 Excessive trading of retail vs institutional investors

Barber and Odean (2001) use household monthly data to study excessive trading of men and women in the sample. The results suggest that both men and women suffer from excessive trading (in the sense that the average monthly abnormal returns for both genders are negative) but men tend to trade more than women. Barber and Odean (2000) uses household data at a large brokerage firm and show that investors in general trade too much. The abnormal returns relative to "own-benchmark" are significantly negative which suggests that investors would be significantly better off if they keep the same portfolio since the beginning of the year. Barber and Odean (2002) also uses household trading data and shows that investors suffer more from excessive trading after switching to an online platform. One drawback of this approach is that it only compares the performance of the observed portfolio to the one of a benchmark which assumes no trading. Suppose one finds that the abnormal net return is positive. This should not imply that the investor does not trade too much. He may still suffer from excessive trading when compared to the optimal level of trade. Additionally, the return on the own-benchmark portfolio is unrealized, i.e., one still needs to pay some transaction cost while selling stocks to realize a part of this return. On the contrary, some of the return on the observed portfolio has been realized when the investor sells the stocks. Therefore, while comparing the performance of the two portfolios, researchers are more likely to conclude that investors trade too much.

tests that require independence. Bootstrapping is used to estimate the empirical distribution for the difference in average returns.

There is less evidence of excessive trading by professional portfolio managers. It has been documented in Barber et al. (2009) that mutual funds' performance net of cost is still positive even though they have to bear large commissions and transaction taxes.

2.2 Disposition effect

While excessive trading concerns both selling and buying activities, the disposition effect is a common bias concerning investors' selling decisions. The disposition effect is the tendency of investors to sell winning stocks and keep holding losing ones. One might expect a rational US individual investor to liquidate stocks in a way that minimizes taxes when she has no information about the prospects of the stocks. This means that they should postpone realizing taxable gains by holding on to their winning investments. The tendency to realize gains rather than losses may cost investors more taxes than necessary (Odean (1998), Baker and Nofsinger (2010)). Shefrin and Statman (1985) introduce a theoretical framework explaining the empirical evidence of the disposition effect: *prospect theory*; *mental accounting*, i.e., the tendency of agents to "mentally" divide their funds into different "accounts" and treat them separately when making decisions; *regret aversion*, i.e., avoid making decisions that admits their earlier mistakes; and *self-control*, i.e., the mechanism employed by investors to force themselves making more rational decisions. In practice, the empirical measures for the disposition effect used in many studies are mainly based on the proportion of gains and losses realized proposed by Odean (1998) or regression method as in Grinblatt and Keloharju (2001) to control for investors' characteristics and market condition.

2.2.1 Proportion of gain and losses realized

Odean (1998) proposes a simple method to measure the disposition effect among individual investors. The idea is to compare the proportion of gains and the proportion of losses that are realized. If the former proportion is significantly higher than the latter, we can conclude that the investors in the sample tends to sell realized gains more than losses.

With this measure, the author differentiates between paper and realized gain or loss. Each day, for every stock in the portfolio that is sold, he compares the average purchase price and the selling price to decide if the stock is sold for a gain or a loss. The gain from selling the stock is referred to as *realized gain* while the loss from selling the stock is referred to as *realized loss*. For every stock in the portfolio that is not sold, he compares the high and low prices on that day with the average purchase price. If the low price is higher than the average purchase price, it is counted as a *paper gain*. If the high price is lower than the average purchase price, it is counted as a *paper loss*.
Compute the proportion of Gains Realized (PGR):

$$PGR = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Paper Gains}} \tag{2}$$

Similarly, compute the proportion of Losses Realized (PLR):

$$PLR = \frac{\text{Realized Loss}}{\text{Realized Losses} + \text{Paper Losses}} \tag{3}$$

If the difference $PGR - PLR$ is large and positive, this means that people tends to sell winning stocks and holds losing ones and thus suggests the presence of a disposition effect.

Odean (1998) uses US trading data from a discount brokerage house. The main hypothesis to be tested is PGR is greater than PLR, which suggests disposition effect among individual investors in the sample. Interestingly, he found that the disposition effect disappears in December. As predicted in Shefrin and Statman (1985), when the self-control mechanism is more explicit, i.e., the end of tax year, it is easier for investors to realize losses. Barber et al. (2007) uses Taiwanese Stock Exchange trading data that includes different types of market participants. They notice the disposition effect among individual investors, corporations and dealers. Dhar and Zhu (2006) uses trading data from a large discount brokerage house and finds that wealthier individuals and those who work in professional occupations are less prone to disposition effect.

This measures based on the proportion of realized gains and losses is more suitable for detecting disposition effect at an aggregate level. At an individual level, it is difficult to contrast the degree of disposition effect among investors with different characteristics. For example, as pointed out in Feng and Seasholes (2005), the difference between PGR and PLR mechanically decreases in the number of stocks in the portfolios, i.e., if one considers the number of stocks a proxy for investors' sophistication, according to this measure, the less sophisticated investors mechanically suffer more from disposition bias while it is not necessarily so. The logit regression and the conditional hazard ratio mentioned in below sections allow us to include control variables such as investors' characteristics and market conditions.

2.2.2 Logit Regressions

Grinblatt and Keloharju (2001) use logit regression to check for the causality between past stock performance and selling decisions, while controlling for other determinants. The dependent variable is a binary one taking the value of 1 if the stock is sold and 0 otherwise. If investors suffer from the disposition effect, they are more likely to sell the stocks that experience good past returns (more likely to realize gains). The independent variables of interest are therefore those related to past positive returns. Specifically, positive return take values $max[0, r_t]$, where r_t is the market-adjusted return on day t. Returns of several time intervals are included, from several days to one year before the trades. Similarly, they also test whether investors are less likely to sell stocks that experience bad past performance (hesitate to realize losses) by including negative return variable. Control variables include dummies for each stock, calendar effect, number of stocks in portfolios, life cycle effects, and market returns.

Grinblatt and Keloharju (2001) use daily trading data for Finnish retail and institutional investors. They show that investors are more likely to sell stocks that have good performance within the last month and less likely to sell stocks with bad performance. They also characterize the functional form of the disposition effect by including dummies for extreme and moderate capital losses and find that individuals are particularly reluctant to sell extreme capital losses. Interestingly, the disposition effect is found across different types of investors including non-financial and financial institutions, households, not-for-profit institutions, and governments. Chang et al. (2016) show evidence of a disposition effect by retail investors only for individual stocks but not on the trading of mutual funds. They explain it by the fact that investors avoid realizing losses because they dislike admitting past mistakes, but delegation reverses this effect by allowing the investor to blame the manager instead.

2.2.3 Conditional Hazard Rate Models

Hazard Rate models are similar to Logit regressions, but allows a more straightforward interpretation of the regression coefficients.

As in Logit regressions, the left-hand side variable is an indicator taking value of 1 if the stock is sold and 0 otherwise. The regression is of the following form:

$$h(t, p, X, Z_t) = h_0(t, p)exp(X\beta + Z_t\gamma + \epsilon_t) \tag{4}$$

Where X includes time-invariant characteristics and Z_t includes time-varying returns (usually X and Z_t are sets of dummies[7]). We are interested in the elements in γ that are associated with past stock performance. $h_0(t)$ is the baseline hazard rate which gives the likelihood of a stock being sold in period t without knowing further characteristics including the past performance. p is the parameters of the baseline hazard rate[8].

Past stock performance can be presented by a set of K dummies for k range of return[9] After estimating (4), one can compute the hazard ratio for the k^{th} range:

$$\frac{h_0(t, p)exp(X, z_{t,k} = 1, z_{t,-k} = 0)}{h_0(t, p)exp(X, z_{t,k} = 0, z_{t,-k} = 0)} = exp(\gamma_k) \tag{5}$$

[7]It is also possible to include numeric variables for past returns, see, for example, Coval and Shumway (2005), IVKOVIC et al. (2005)

[8]One can assume a functional form for $h_0(t)$, for example the Weibull function, and estimate the parameters as in Feng and Seasholes (2005) or make no assumption about the change in the baseline hazard rate through time, i.e., The Cox proportional hazard model, and simply obtain this rate from the data, as in Barber and Odean (2013)

[9]For example, in Barber and Odean (2013), the possible range of return is divided into many narrower range, i.e., ..., $-6\% < r \leq -2\%$, $-2\% < r \leq 2\%$, $2\% < r \leq 6\%$,.... so the element z_{tk} takes value of 1 if return in period t falls into range k. They use the range $-2\% < r \leq 2\%$ as the baseline (omitted) category, therefore the interpretation of the coefficients related to past returns will be relative to this category. Feng and Seasholes (2005) use a trading loss indicator and a trading gain indicator capture the past performance.

where $z_{t,k}$ is the dummy variable for range k and $z_{t,-k}$ is the dummies for all ranges except k. $exp(\gamma_k)$ corresponds to the k^{th} return range tells us how much more/less likely the stock is being sold in period t relative to the reference range (for example, $-2\% < r \leq 2\%$ as in Barber and Odean (2013)), keeping constant other characteristics.

2.2.4 Disposition Effect among Retail and Institutional Investors

Barber and Odean (2013) use Finnish data as well as the one from a large discount brokerage firm and show that the likelihood of a stock being sold strongly increases with positive past returns. Negative past returns of a larger magnitude also increase the likelihood of being sold but not as strongly as positive returns, which shows that investors do realize their losses, but not as much as their gains. Feng and Seasholes (2005) use account level data from a Chinese national brokerage firm and show that overall, a stock is more (less) likely to be sold if it experiences past positive (negative) returns, relative to the time-varying baseline hazard rate. Additionally, the study gives evidence that sophisticated investors are less prone to the disposition effect and the combination of sophistication and trading experience eliminates investors' reluctance to realize losses[10]. Interestingly, Ivković and Weisbenner (2009) using same brokerage firm data set analyzed by Barber and Odean (2000) to study the relation between mutual fund flows and fund characteristics and document that individual investors are reluctant to sell mutual funds that have appreciated in value and are more willing to sell losing funds, which is consistent with tax motivations. Using the same data set, Bailey et al. (2011) calculate several measures of behavioral biases for each investor and relate these to their behavior regarding mutual fund shares. They find that investors suffering from the disposition effect in their common stock trades are less likely to invest in equity mutual funds. Conditional on investing in mutual funds, disposition investors select funds with higher expenses and time their purchases and sales poorly. These results suggest that mutual fund investors are, on average, more sophisticated than those who hold only common stocks. This could explain the absence of disposition effects reported in Ivković and Weisbenner (2009). Kumar and Lim (2008) find that investors who tend to execute several trades during the same day also suffer less from the disposition effect. The authors argue that such investors are more likely to consider what is good for the overall performance of their stock portfolio (broad framing) instead of focusing on each stock separately (narrow framing). Kumar (2009) investigates stock level determinants of the disposition effect and found that the disposition effect is stronger for stocks with higher idiosyncratic volatility, lower market capitalization, higher turnover, weaker price momentum, lower institutional ownership, lower prices, and higher bid-ask spreads. The author argues that this is consistent with the disposition effect (and investment mistakes in general) being

[10]Note that the disposition effect does not seem to be related to the type of investors' taxation as it can be detected in both taxable and tax-deferred accounts (IVKOVIC et al. (2005))

stronger among stocks that are more difficult to value.

Barber et al. (2007), using trading data of different types of investors on the Taiwan Stock Exchange, shows that, unlike individual investors, corporations and dealers or local mutual funds are not reluctant to realize losses versus gains. Similarly, Cici (2012) documents that, on average, US (equity) mutual fund managers are not prone to the disposition effect. On the contrary, they tend to realize losses more readily than gains. However, they also show that the disposition effect is more pronounced among funds that have pressure to act on their portfolio due to investor redemptions. Using a proprietary currency trades database, O'Connell and Teo (2009) show that large institutional investors in the foreign exchange markets are not susceptible to disposition effects. On the contrary, these investors are more likely to decrease their risk exposure after a loss and increase their risk exposure after a gain.

Frazzini (2006) uses data on mutual fund holdings of all registered mutual fund holdings filing with the SEC plus three thousand global funds. He shows that mutual fund managers, on average, have a higher tendency to sell winners compared to losers, although the magnitude is smaller than the one of retail investors. Interestingly and consistent with Cici (2012), loser funds are more prone to disposition effect, with a magnitude as large as retail investors as reported in Odean (1998). Similarly, using the sample of shareholdings for all investors registered to IPOs and those who purchase the Australian Stock Exchange (ASX) index, Brown et al. (2006) document the disposition effect is robust across institutional investors (incorporated companies, insurance companies, superannuation funds, governments) and retail investors. The effect is however weakened as the holding period increases. Grinblatt and Keloharju (2001) finds the evidence of disposition effects across different types of investors including financial institutions. The disposition effect is also documented among professional futures traders on the Chicago Mercantile Exchange or the Chicago Board of Trade (Locke and Mann (2005), Coval and Shumway (2005).

Although the disposition effect is well documented among both individual and institutional investors, the majority of evidence is mainly among single asset portfolios. Another interesting question is to study whether the magnitude of the disposition effect depends on market condition and investors' wealth.

2.3 Home bias

Despite the widely recognized benefit of international diversification of equity portfolio (see, for example, Grubel (1968) and Levy and Sarnat (1970)), one of the most striking feature of international portfolio investment is the tendency of investors to hold portfolio biased towards domestic equities compared to foreign ones (French and Poterba (1991), Tesar and Werner (1995), Kang et al. (1997)). This tendency is called "home bias". Baker and Nofsinger (2010) and Barberis (2018) suggest several rational motivations and behavioral biases that are behind this bias[11]. There are two main approaches to identify/measure home biases, the model-based approach and the data-based approach (Baker and Nofsinger (2010)). Each has its strengths and weaknesses.

2.3.1 ICAPM equilibrium weights

One way to identify home bias is to compare one's portfolio with the one derived from the international capital asset pricing model (ICAPM). Under the model assumptions, expected excess returns of an asset should be proportional to its exposure to the world market portfolio, i.e., the portfolio in which the weight of each country is the ratio of its market capitalization to the world market capitalization. A difference between the weights (of domestic equity or foreign equity) of an observed portfolio and the ones of the world portfolio suggests a bias.

For each of the host country i (country of the investors), calculate the percentage of holdings in each country j, w_{ij}:

$$w_{ij} = \frac{MV_{ij}}{\sum_{j=1}^{N} MV_{ij}} \tag{6}$$

where MV_{ij}: market value of holdings of country j for host country i and N is the number of countries where investment can be made.

Compute the weight of country j in the world market portfolio:

$$w_j^* = \frac{MV_j^*}{\sum_{j=1}^{N} MV_j^*} \tag{7}$$

where MV_j^* is the market capitalization of country j.

The home bias measure, $\frac{w_{ij}}{w_j^*}$ where $i = j$ that exceeds 1 suggests the presence of home bias.

Based on national account statistics, Cooper and Kaplanis (1994) show that portfolio holdings of domestic equity of investors across eight OECD countries account for 64% to 100% of their portfolio. In contrast, these countries' market capitalization accounts for only 0.8 to 43.7% of the total market capitalization of the eight countries. Additionally, they show that home bias cannot be explained by investors hedging domestic inflation risk or the dead-weight costs they have to bear for cross-border transactions. Similarly, Chan et al. (2005) use mutual fund holding data in 26 countries and confirm the presence of home bias in portfolio holdings of fund managers across these countries. As an extreme example, Greece fund managers, on average, allocate 93.5% of their portfolio to domestic equity while the proportion of Greece's market capitalization in the world portfolio is only 0.46%. However, they also document

[11] Rational explanations include hedging against domestic risks, currency risk, higher transaction costs for trading foreign stocks, investing in multinationals and larger asymmetric information for foreign stocks. Behavioral explanations include failing to assess risks, overconfidence, regret, patriotism, and social identification (Baker and Nofsinger (2010)) and ambiguity aversion (Barberis (2018)).

some exceptions for countries of the same continents or regions: fund managers show some tendency to overweight equity of their neighbor countries relative to countries with further geological distance. In Lütje and Menkhoff (2007), a survey of German fund managers suggests the majority of them prefer a weight of 10% for German shares. This is to contrast with the country's share of the world market capitalization of only 3%. Karlsson and Nordén (2007) study Swedish employees' allocation to domestic and foreign mutual funds in their pension plans. An average employee allocates 34% of his investment in domestic mutual funds while the domestic share of all available funds is only 24%. Additionally, they show that not so wealthy older men who work for the government and hold no other risky assets are the ones most likely associated with the home bias. Home bias is also documented in Fidora et al. (2007) on portfolio holdings data in 70 countries, in Sørensen et al. (2007) on both stock and bond holdings in 18 countries.

Despite the simplicity of this approach, the ICAPM equilibrium portfolio does not necessarily perform well historically and this may be the reason why observed investors' weights differ from the ICAPM. Instead of comparing the observed weight with the ICAPM equilibrium weights, one can consider the optimal weights obtained from a Markowitz portfolio optimization using historical data.

2.3.2 Home bias among Retail and Institutional Investors

Tesar and Werner (1995) derives the optimal portfolio for stock and bonds across five OECD countries and shows that the share of foreign assets in observed portfolios is considerably smaller than those predicted by the theory. Estimating the implied expected returns of equity of each country based on the observed portfolio, they also show that investors are consistently more optimistic about returns on the domestic market relative to those on the foreign market. Specifically, in their data sample, investors think that the expected return in their own country is from 170 to 420 basis points higher compared to the world market portfolio. Lewis (1999) shows that the minimum variance portfolio based on the US and non-US index returns composes of about 40% of foreign assets while the observed allocation to foreign assets in US portfolio holdings is only 8%. French and Poterba (1991) estimate the expected real returns implied by the observed portfolio holding of investors in the US, Japan, and the UK. They document a substantial difference in expected returns by domestic versus foreign investors.

There is evidence that institutional investors also suffer from home bias. Chan et al. (2005) confirm the presence of home bias among fund managers across 26 countries. Similarly, using survey data, Lütje and Menkhoff (2007) document home bias among fund managers in Germany although the magnitude of this bias is smaller compared to those of retail investors. Consistent with Lütje and Menkhoff (2007), Hau and Rey (2008) show that the degree of home bias among mutual funds is less than the aggregate level for all investors. They also document considerable heterogeneity across funds. In particular, the degree of bias is positively correlated with fund size. Anderson et al. (2011) document home bias in institutionally managed portfolios in 60 countries and associate the heterogeneity in home bias with cultural characteristics. Notice that there are several rational motivations for home bias. For example, some institutions may have the mandate to hold local assets as a hedge for domestic inflation. Investors may also avoid foreign assets due to currency risk or higher transaction costs. The home bias may also stem from irrational motivations such as ambiguity aversion. Without data on the constraints faced by investors (as in the above studies), it is difficult to distinguish between these two types of motivations.

3 Conclusion

This short note presents important biases in investors' beliefs and preferences and discusses the empirical methods to measure investors' biases from trading activities. Most of the biases we described are largely present among retail investors and to a less extent among institutional investors. They can have large consequences on investment decisions and reduce investors' performance. Once identified, bias systematic detection systems can be integrated into trading platforms to alert investors, potentially reducing the amplitude and likelihood of the biases.

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