



Measuring costly behavioral bias factors in portfolio management: a review

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Abstract

Various factor models extended by Jensen's (J Financ 23:389–416, 1968) alpha have been used to measure the retail investors' portfolio (under-) performance compared to the market portfolio. The previous studies tried to explain this anomaly in behavioral finance by examining retail investors' cognitive biases that induce irrational trading behavior. While operationalizing these cognitive biases in trading is not trivial, researchers still have found measures to proxy for biases and prove their statistical and economic significance. However, these studies only focused on linking one or a subset of behavioral biases and their effect on portfolio performance. In addition, different measures of biases across studies complicate the comparability of results. Therefore, this paper provides a structured overview of the current state of the literature regarding behavioral biases and their measurements to design a behavioral factor model that should help to explain the performance alpha from a behavioral finance perspective. The paper presents an overview of 11 behavioral bias factors and 29 corresponding measurements to consider inputting in such a model. With an application-oriented focus, it is recommended to include the most researched bias factors in a factor model, which are also the most detrimental to portfolio performance, as well as to include the most frequently used and least complex measures, which results in the primary inclusion of the following eight behavioral bias factors: disposition effect, under-diversification, home bias, local bias, lottery stock preference, trend chasing, overtrading, and trade clustering.

Keywords Behavioral finance · Household finance · Cognitive bias · Factor models · Investment behavior · Portfolio management

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1 Introduction

As history proves that the market outperforms the average retail investor, what is driving investors to deviate from classic buy-and-hold strategies of market indices? In Traut's (2023) review, he names the most prevailing causes for this anomaly: exposure to coskewness risk, investor constraints, agency problems, and behavioral biases. This paper focuses on behavioral biases, trying to understand better why people make certain choices and what can be done to improve those choices from a behavioral finance perspective because when making financial decisions like investing, we are less rational than traditional finance theory predicts. Thus, instead of making the best (rational) choices, we often make facilitated choices based on heuristics that are rather satisfactory to our individual preferences (e.g., mental compartments) than rational. Cognitive biases induce this irrational investment behavior as our (bounded) rationality is limited by our thinking capacity, the information that is available to us, and time (Campitelli and Gobet 2010; Kahneman 2003).

Much research has followed Campbell's (2006) call to financial economists to work on insights that improve individual investors' decision-making. For instance, there is evidence that financial education programs may improve individuals' financial decision-making (Fox et al. 2005). Yet, the average level of financial literacy continues to be low (Lusardi and Mitchell 2014). Programs such as the "Save More Tomorrow" plan (Thaler and Benartzi 2004), which target and exploit specific behavioral biases, therefore appear to be a promising alternative. Financial advice, on the other hand, is often found not to help investors, either because it is subject to agency conflicts and may be biased due to the service's commission and fee structure (Hackethal et al. 2012; Inderst and Ottaviani 2009), because financial advisors themselves are affected by cognitive biases, e.g., loss aversion (Eriksen and Kvaløy, 2010), or because investors do not adhere to it (Bhattacharya et al. 2012).

If behavioral biases are detrimental to investment performance, how can we help avoid them?

First, by raising awareness of their presence. The impact of behavioral biases must be tangible (measurable) such that investors and financial advisors may understand the link between the bias exposure and its costly effect on their portfolio performance. Measuring the exposure to these cognitive limitations is not trivial, but research has found ways (proxies) to operationalize investment behaviors, which will be presented and discussed in Sects. 3 and 4.

Second, these behavioral biases must be integrated into a holistic performance attribution model so that investors can recognize the underperformance's origin. A performance attribution model typically includes at least one performance factor and an additional performance measure. The most famous and widely accepted performance measure is Jensen's alpha (Jensen 1968), which determines the abnormal return of a security or portfolio of securities over the theoretical expected return. For

example, in the context of asset pricing, the Capital Asset Pricing Model (1) uses a market factor (expected return of the market) and a sensitivity factor beta to determine a theoretically appropriate rate of return for an asset (Sharpe 1964). Then, the alpha measures the idiosyncrasy of a given retail investor's portfolio compared to the market portfolio. Further factor models (2)–(4) include the three-factor model (Fama and French 1993), the four-factor model (Carhart 1997), and the five-factor-model (Fama and French 2015), which also include factors regarding the firms' characteristics held: small minus big (SMB), high minus low (HML), the momentum (MOM), robust minus weak (RMW), or the conservative minus aggressive (CMA) factor. In addition, Daniel et al. (2020) proposed a three-factor (5),¹ including a financing (FIN) and post-earnings announcement drift (PEAD) anomaly factor.

$$(R_i - R_f) = \beta_{iM} * (R_m - R_f) + \alpha_j \quad (1)$$

$$(R_i - R_f) = \beta_m * (R_m - R_f) + \beta_{smb} * SMB + \beta_{hml} * HML + \alpha_j \quad (2)$$

$$(R_i - R_f) = \beta_m * (R_m - R_f) + \beta_{smb} * SMB + \beta_{hml} * HML + \beta_{mom} * MOM + \alpha_j \quad (3)$$

$$(R_i - R_f) = \beta_m * (R_m - R_f) + \beta_{smb} * SMB + \beta_{hml} * HML + \beta_{rmv} * RMW + \beta_{cma} * CMA + \alpha_j \quad (4)$$

$$(R_i - R_f) = \beta_m * (R_m - R_f) + \beta_{fin} * FIN + \beta_{pead} * PEAD + \alpha_j \quad (5)$$

In the respective equations, the alpha quantifies the abnormal return of a portfolio compared to the included factors in the mentioned models, and any deviation from these models ($\alpha_j \neq 0$) can be seen as idiosyncratic because these models tend to explain roughly 95% of the achieved portfolio returns (Carhart 1997; Daniel et al. 2020; Fama and French 2015, 1993). However, these models assume that retail investors hold a diversified portfolio and disregard transaction costs (trading frequency), whose costly presence is discussed in Sect. 4. Therefore, it is suggested to further examine the idiosyncratic component of these models, the alpha component, by considering behavioral biases to derive the explanations for the performance deviations from the mentioned factor models above. The determined variable (alpha) should be explained as a function of multiple behavioral bias factors multiplied by a sensitivity factor beta.

¹ Daniel et al. (2020) proposed a “Behavioral Factor Model” consisting of two factors based on thirty-four anomalies (firms' characteristics), PEAD proxying for short-term anomaly (limited attention) constructed by going long firms with positive earnings surprises and short firms with negative surprises and FIN for long-term anomaly (overconfidence) by considering a composite of the 1-year net-share-issuance (NSI) and 5-year composite-share-issuance (CSI) measures. Daniel et al. (2020)'s approach is different from this paper: Their overall goal was to examine mispricing in financial markets based on firms' financials, while this paper provides bias factors to examine portfolio return anomalies (the alpha component of the mentioned models) of retail investors based on retail investors' bias-induced trading behaviors. However, similarly to the other named factor models (1)–(4), the bias factors provided in this paper could enhance the applicability of the model (5) on retail investors by explaining its alpha component. In comparison with (1)–(4), the factors FIN and PEAD must be calculated manually.

$$\alpha_j = \beta_1 * \text{BIAS}_1 + (\dots) + \beta_n * \text{BIAS}_n + \varepsilon \quad (6)$$

Eventually, a visual presentation of the alpha return decomposition into multiple investment behaviors in a financial tool would help the user (retail investor and financial advisor) to realize the implicit costs of specific behavioral biases in portfolio choice and management and would consequently enable appropriate actions to mitigate those.

Hence, this paper should provide the foundation further to explain the factor models' idiosyncratic component alpha. Therefore, two requirements for a holistic evaluation of behavioral biases are defined, which align with the mutually exclusive and collectively exhaustive (MECE) principles (Minto 2002): First, a holistic approach implies the collective exhaustiveness of the behavioral biases considered. Therefore, an extensive literature review was conducted. Second, mutual exclusiveness means that behavioral biases do not overlap. As this paper performs a qualitative assessment of empirical studies, there will be no quantitative examination of correlations. However, in the conclusion of this paper, a reduced number of behavioral bias factors are suggested based on the maturity of the research of the respective biases and based on the validated economic significance in numerous studies.

This paper contributes to the intention of policymakers and financial advisors to improve programs or measures intended to make investors aware of their costly investment behaviors and subsequently enhance their financial choices and, thus, investment performance. Additionally, this paper provides an extensive review of existing behavioral biases, which enables the holistic and systematic examination of behavioral biases in portfolio choice and management in the future research.

The remainder of this paper is structured as follows. Section 2 provides the methodology, and Sect. 3 collects empirical evidence in various settings. Section 4 lists and discusses the results. Finally, Sect. 5 provides a conclusion of the findings.

2 Methodology

A systematic review of the international literature on behavioral biases in trading was performed according to the PRISMA method (Moher et al. 2009) for studies published in two electronic databases: Google Scholar and the University Library RWTH Aachen. The review focused on identifying a set of operationalizations of investment behaviors (bias factors) and their effect on portfolio performance in quantitative studies. The search was performed by combining keyword blocks such as "investment behavior," "investment bias," or "cognitive bias" with "operationalization," "measure," "private investor," or "behavioral finance." Additional studies were identified by following references that met the inclusion criteria. The flowchart of this process is shown in Fig. 1.

The selected studies were eligible if they met the following inclusion criteria: (1) They had to be either relevant (high number of citations) or recent (recently published studies), (2) they had to conduct quantitative measurements of investment behaviors, and (3) they had to be written in either English or German.

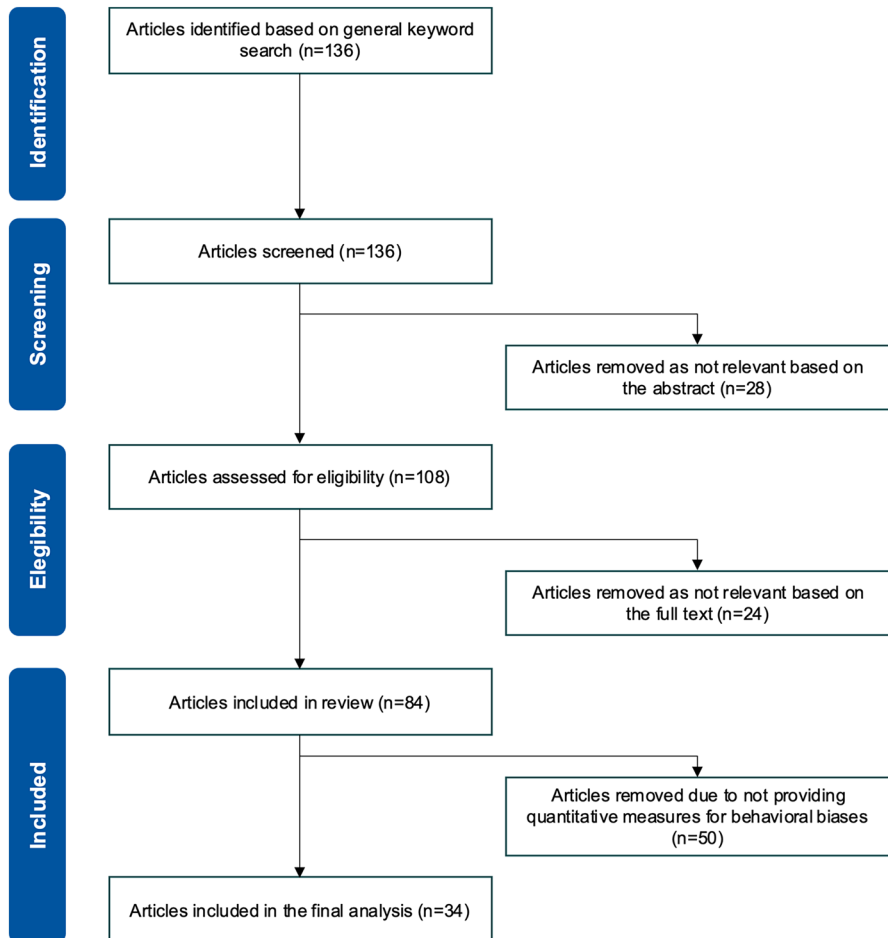


Fig. 1 PRISMA flow diagram (Moher et al. 2009)

After identifying relevant studies with the keyword search, the identified studies were merged and initially screened for eligibility based on their titles and abstracts. Then, full-text studies were further assessed for eligibility, i.e., checked that the inclusion mentioned above criteria was satisfied.

3 Results

The keyword search initially led to a total of 136 studies. Twenty-eight of these 136 studies were excluded from screening the initial abstract, and 24 were excluded from screening the complete text because they were assessed against the inclusion criteria. The remaining 84 studies were reviewed, focusing on bias-induced investment behaviors, their operationalization, and their effect on portfolio performance.

However, 50 of these studies did not provide quantitative measurements and their impact, so these were further excluded from this review. Eventually, a total of 34 studies were included in this systematic review. Table 1 presents the main characteristics of the included studies in this review.

3.1 Publication year and sample data

The review includes 34 studies over 23 years, from 1998 until 2021. No relevant studies were published in 2002, 2003, and 2004. From 1998 until 2009, 17 relevant studies were included with an average of 1720 citations; more recent 17 studies had 300 citations. Most studies were conducted in the USA ($n=22$), followed by studies considering multiple countries ($n=4$), Germany ($n=3$), Finland ($n=2$), and then the Netherlands, Brazil, and Sweden ($n=1$).

3.2 Duration of examinations and target groups

The duration of the examinations varied considerably from 1 to 7 years for retail trading data obtained from brokerage firms ($n=19$) and from 6 to 79 years for publicly available data sets, e.g., stock trading data from stock exchanges and surveys. Whereas the former exclusively analyzed the trading behavior of retail investors, and the latter (publicly data sets, surveys, or stock market simulations) analyzed characteristics of stocks, funds, and indices.

3.3 Bias-induced investment behaviors

The bias-induced investment behaviors included in this review were analyzed, and the results are presented in Tables 1, 2, 3, and 4. The first table (Table 1) provides an overview of the included studies, their characteristics, the examined bias factors and measurements, and their key findings. The second table (Table 2) briefly summarizes the definition of the identified behavioral bias factors, the number of studies that examined them, the total number of measurements, and their effect on portfolio performance. Finally, the third table (Table 3) provides an overview of the measures used to operationalize the behavioral biases in the reviewed quantitative studies, and Table 4 concludes with a recommended shortlist of bias factors and measures.

3.3.1 Operationalized behavioral biases

Eleven bias factors were identified in this review and are described in Table 2, while their measures are presented in Table 3. Bias factors were grouped into three groups based on their similar characteristics to have a comprehensible overview and are introduced by a short description in the following.

Table 1 Review findings—(1) Performance measures and (2) considered behavioral bias factors, measurements* and effect on portfolio performance (*Further described in Table 3)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Odean 1998)	1987–1993	USA	Brokerage data	Retail investors	Raw return, excess return	Disposition Effect (1.2) → Negative	Investors keeping both stocks (winners and losers) outperform the disposition effected investors (that keep only the losers) by 2.35% p.a. For winners that are sold, the average excess return over the following year is 3.4% more than it is for losers that are not sold
(Dhar and Zhu 2006)	1991–1996	USA	Brokerage data	Retail investors	N/A	Disposition Effect (1.2) → N/A Under-diversification (2.1) → N/A	Wealthier individuals and individuals employed in professional financial occupations exhibit a lower disposition effect Trading frequency tends to reduce the disposition effect
(Kumar and Lim 2008)	1991–1996	USA	Brokerage data	Retail investors	Alpha, raw return, Sharpe ratio	Disposition Effect (1.2) → Negative Under-diversification (2.3) → N/A Overtrading (8.1) → N/A Trade Clustering (10.1) → Negative	Investors underperform the common performance benchmarks by 4.32% p.a. Investors with the highest trade clustering (and thus the broadest framing) have a monthly alpha of -0.271% and those investors with the lowest TC (and thus the narrowest framing) have a monthly alpha of -0.407% (delta equals 1.632% p.a.)

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Bailey et al. 2011)	1991–1996	USA	Brokerage data	Retail investors	Alpha, raw return, Sharpe ratio	Disposition Effect (1.2) → Negative Trend chasing (6.1) → N/A Local Bias (4.1) → Negative Lottery Stock Pref. (5.1) → Negative Lottery Stock Pref. (5.3) → Negative Narrow Framing (10.2) → Negative Inattention to Earning News (11.1) → Negative Inattention to Macroeconomic News (11.2) → Negative Overconfidence (9.1) → Negative	Investors on average have a mean monthly alpha of -0.375% , which translates into risk-adjusted underperformance of 4.50% p.a. Mean monthly return is lower by -0.041% per month for each standard deviation increase in narrow framing (2.12% p.a. lower return for the highest narrow framing group compared to the lowest narrow framing group) Analogous 1.34% p.a. difference between the extreme quintiles of disposition effect
(Chang et al. 2016)	2015	USA	Brokerage data	Retail investors	N/A	Disposition Effect (1.5) → N/A Under-diversification (2.1) → N/A	Larger cognitive dissonance results in higher magnitude of disposition effect (classic and reverse) Investors are more likely to sell again in months in which at least one sale is executed For funds, investors are less likely to sell if it is a gain (reverse disposition effect)
(Han and Kumar 2013)	1983–2000	USA	Brokerage data	Retail investors, stocks	Alpha, raw return	Disposition Effect (1.2) → N/A Disposition Effect (1.3) → Negative Lottery Stock Pref. (5.1) → Negative	The annualized characteristic- and risk-adjusted RTP premium estimates are both about -7% Speculative retail trading affects stock prices

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Da Costa et al. 2013)	1997–2001	Brazil	Stock market simulation	Retail investors and undergraduate students	N/A	Disposition Effect (1.2) → N/A Disposition Effect (1.1) → N/A Disposition Effect (1.4) → N/A	69,2% of the subjects have a disposition effect greater 0% More experienced investors are less affected
(Seru et al. 2010)	1995–2003	Finland	Brokerage data	Retail investors	Raw return	Disposition Effect (1.6) → N/A	Evidence of two types of learning: some investors become better at trading with experience, while others stop trading after realizing that their ability to trade is poor Investors whose performance are one standard deviation worse than the mean are about 15% less likely to continue trading
(Meyer et al. 2012a)	2000–2007	Germany	Brokerage data	Retail investors	Alpha, Sharpe ratio modified Dietz method	Disposition Effect (1.2) → N/A Under-diversification (2.1) → N/A Under-diversification (2.2) → N/A Overtrading (8.1) → N/A	Investors learn (improve their performance) by trading: 100 additional active trades are associated with an increase in portfolio performance of 0,15% per month One additional month of active trading is associated with an increase in monthly portfolio returns by 0,02% (0,24% p.a.)

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Weber et al. 2014)	1999–2011	Europe	Brokerage data	Retail investors	Alpha, raw return, Sharpe ratio	Disposition Effect (1.6) → Positive Trend chasing (6.1) → Positive Under-diversification (2.2) → Negative Under-diversification (2.3) → Negative Home Bias (3.2) → Positive Local Bias (4.1) → Positive Lottery Stock Pref. (5.2) → Negative Overtrading (8.1) → Negative Narrow Framing (10.1) → Positive Leading Turnover Share (7.1) → Negative	The mean investor has a 4.2% lower annual portfolio returns than a fully diversified investor Lottery stock preference costs an investor 3.31% p.a. while low trade clustering (narrow framing) improves performance by 2.13% p.a. For funds, trend chasing improves performance by 1.09% p.a.

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Goetzmann and Kumar 2008)	1991–1996	USA	Brokerage data	Retail investors	Monthly excess return, Sharpe ratio	Disposition Effect (1.2) → N/A Trend chasing (6.1) → N/A Under-diversification (2.1) → Unclear Under-diversification (2.2) → Unclear Under-diversification (2.3) → Unclear Local Bias (4.2) → Unclear Overtrading (8.1) → Unclear Overconfidence (9.1) → N/A	The lowest diversified decile has a lower alpha of 0.12% per month (1.44% p.a.) than the highest diversified decile Under-diversification is costly to most investors, but a small subset of investors under-diversified because of superior information Investors who trade excessively, tilt their portfolios toward local stocks, and are sensitive to past price trends exhibit greater under-diversification as well as earning lower returns Most surprisingly, high-turnover, under-diversified portfolios perform better than high-turnover, better-diversified portfolios
(Calvet et al. 2006)	1999–2002	Sweden	Includes all trading data in Sweden	All individual investors	Alpha, Return loss, Sharpe ratio loss	Under-diversification (2.4) → Negative	A subset of the sample loses up to 10% p.a. due under-diversification and 4.3% p.a. for being too risk averse Sophisticated investors invest more efficiently and aggressively (higher risk appetite) Most households outperform the domestic benchmark via international diversification Diversification is supported by funds (76% of investors hold funds as well as stocks)
(Grinblatt et al. 2011)	1995–2002	Finland	Includes all trading data in Finland	All individual investors	Sharpe ratio	Under-diversification (2.1) → N/A	Higher IQ leads to a higher Sharpe ratio (mainly because of a lower volatility), more stocks held and a higher probability for a fund to be held (leading to a more diversified portfolio)

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Gaudefcker 2015)	2005–2006	Netherlands	Dutch household survey	All individual investors	Sharpe ratio	Under-diversification (2.4) → Negative	The market coefficient rises continuously with the return loss meaning that riskier portfolios have lower return The average return loss of an investor is 0.552% p.a. (risk-adjusted loss compared to the market) Largest losses resulting from under-diversification are incurred by those who neither turn to external help with their investments nor have good skills in basic financial-numerical operations and concepts
(Graham et al. 2009)	1999–2002	USA	UBS/Gallup Investor Survey	Retail investors	N/A	Home Bias (3.3) → N/A	When an investor feels competent about understanding the benefits and risks involved in investing in foreign assets, he is more willing to invest in foreign securities. In contrast, when an investor feels less competent, he is more likely to avoid foreign assets High competence (assessed by the investors themselves) correlates with higher trading frequency
(Von Nitzsch, R. and Stotz, O., 2005)	1979–2005	Multiple	Previous studies	Indices	Sharpe ratio, return for a given volatility	Home Bias (3.1) → Unclear	A higher international diversification leads to a higher return For investors in countries with a high market capitalization and a developed capital market, such as the US, the UK, and Japan, the loss in returns can be expected to be lower than 1% p.a.; for Germany, France, Italy, and Canada, the costs from a home bias are even likely to be higher than 1% p.a. For the USA, home bias even indicated a positive impact on performance

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Coourdacier and Rey 2013)	2008	Multiple	Publicly available data sets	Indices	N/A	Home Bias (3.4) → N/A	The average home bias is 0.63 across multiple countries being lower in Europe (about 0.5) and higher in emerging markets (0.9) Home bias has become less and less over time
(Coval and Moskowitz 2001)	1975–1994	USA	US mutual funds data	Mutual fund managers	Raw returns, Alpha	Local Bias (4.2) → Positive	Local investments of fund managers achieve an excess return of 2.67% p.a. compared to non-local stocks—although the Sharpe ratio is not different (meaning local investments are also riskier)
(Ivković and Weisbenner 2005)	1991–1996	USA	Brokerage data	Retail investors, stocks	Alpha, raw return, excess return	Under-diversification (2.1) → N/A Local Bias (4.1) → N/A Local Bias (4.2) → Positive	The average household generates an additional return of 3.7% per year from its local holdings relative to its non-local holdings, suggesting that local investors are able to exploit local knowledge The excess return to investing locally is even larger among stocks not in the S&P500 index (firms where informational asymmetries between local and non-local investors may be largest), while there is no excess return earned by households that invest in local S&P500 stocks
(Seasholes and Zhu 2010)	1991–1996	USA	Brokerage data	Retail investors	Alpha, excess return	Local Bias (4.2) → Positive	Distance to own portfolio is on average 308 miles lower than to the market portfolio Share of local stocks in investor's portfolio is 30% (overweight), while only 12% of the market is head-quartered within the same radius Investors local portfolios outperform the market by 0.8% p.a.

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Kumar 2009)	1991–1996	USA	Brokerage data	Retail investors, stocks	Alpha, raw return	Lottery Stock Pref. (5.1) → Negative Lottery Stock Pref. (5.2) → Negative Lottery Stock Pref. (5.4) → N/A	Lottery stocks have a monthly alpha -0.52% p.m. (-6.23% p.a.) The risk-adjusted performance difference between lottery and non-lottery stocks is -7.1% p.a. Lottery stocks have roughly double the standard deviation compared to non-lottery stocks Lottery stocks make up 3.74% of an average retail portfolio and only 0.76% of an average institutional portfolio As a group, lottery-type stocks represent 1.25% of the total stock market capitalization, but in terms of their total number, they represent about 13% of the market Lottery stocks are determined based on the maximum daily return over the past one month (MAX)
(Bali et al. 2011)	1926–2005	USA	Stock exchange data	Stocks	Alpha	Lottery Stock Pref. (5.1) → Negative	The alpha of the lowest decile MAX-portfolio is 1.18% p.m. (14.16% p.a.) higher than of the highest decile MAX-portfolio
(Bali et al. 2017)	1963–2012	USA	Stock exchange data	Stocks	Alpha	Lottery Stock Pref. (5.1) → Negative	The alpha of the lowest decile MAX-portfolio is 1.4% p.m. (16.8% p.a.) higher than of the highest decile MAX-portfolio. Lower MAX means lower lottery characteristics
(Bali et al. 2021)	1963–2017	USA	US stock exchange data	Stocks	Alpha	Lottery Stock Pref. (5.1) → Negative	The highest decile of lottery characteristics portfolio has a -0.71% p.m. (-8.52% p.a.) lower monthly alpha than the lowest decile Consistent with previous evidence that lottery demand is attributable to individual, not institutional, investors, the beta anomaly is concentrated among stocks that have low institutional ownership

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Bergsma and Tayal 2019)	1988–2015	USA	Stock exchange data	Stocks	Alpha	Lottery Stock Pref. (5.1) → Negative	The highest lottery stock quintile of high RSI (relative short interest) stocks has a four-factor alpha of -1.61 % p.m. (-19.32% p.a.) Weaker arbitrage in high RSI lottery stocks leads to overpricing of the stocks
(Odean 1999)	1987–1993	USA	Brokerage data	Retail investors	Alpha	Overtrading (8.1) → Negative	The purchases of investors underperform their sales by an average return of 3.31% p.a. Returns of sold stocks are statistically significantly higher than bought stocks
(Barber und Odean 2001)	1991–1996	USA	Brokerage data	Retail investors	Alpha	Overtrading (8.1) → Negative	Men have a monthly portfolio turnover of 6.41% while women have 4.4% (Difference of 2.01%) Both men and women achieve a lower return by trading The stocks they sell earn reliably greater returns than those they buy (men: 2.4% p.a.; women: 2.04% p.a.)
(Barber and Odean 2000)	1991–1996	USA	Brokerage data	Retail investors	Alpha, raw return	Overtrading (8.1) → Negative	The average household underperforms the market by 1.5% p.a. High trading turnover costs households 6.8% p.a. relative to the returns earned by low turnover households
(Fischbacher et al. 2017)	2015	Germany	Stock market simulation	Students	N/A	Disposition Effect (1.2) → N/A	In the experiment, automatic selling devices helped investors increase the proportion of losers realized but did not affect the proportion of winners realized still leading to a reduction of the disposition effect

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Dhar and Kumar 2001)	1991–1996	USA	Brokerage data	Retail investors	Raw return	Disposition Effect (1.2) → Unclear Disposition Effect (1.3) → Unclear Under-diversification (2.1) → N/A Trend chasing (6.1) → Unclear	For contrarian investor group, the average 21-day return for the stocks they sell is significantly higher (8.84%) than the average 21-day return for stocks they hold (1.78%). In contrast, the average 21-day return for the stocks the momentum investors sell is significantly lower (−2.98%) than the average return for stocks they hold (1.40%)
(Sirri and Tufano 1998)	1971–1990	USA	Publicly available data sets	Flow of funds	Alpha, excess return	Trend chasing (6.1) → N/A	High performance appears to be most salient for funds that exert higher marketing effort, as measured by higher fees. Flows are directly related to the size of the fund's complex as well as the current media attention received by the fund, which lower consumers' search costs Consumers of equity funds disproportionately flock to high-performing funds while failing to flee lower-performing funds at the same rate

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Ivković et al. 2008)	1991–1996	USA	Brokerage data	Retail investors	Alpha, Sharpe ratio	Under-diversification (2.1) → Positive Under-diversification (2.2) → Positive Local Bias (4.2) → Positive Overtrading (8.1) → N/A	Concentrated portfolios of individual investors outperform diversified portfolios which implies a successful exploitation of information asymmetries Concentrated households have a 0.16% p.m. (1.92% p.a.) higher alpha than diversified portfolios Portfolios with fewer stocks have a higher return than those with more stocks but they are associated with higher risks and a lower Sharpe ratio Results are not driven by specialization in a particular industry, inside information, broad market timing, repeated trades in a particular stock, or regional differences across investors. Rather, the results seem to reflect that wealthy households who concentrate their holdings in a few stocks tend to have the ability to identify superior stock picks
(Meyer et al. 2012b)	2005–2010	Germany	Brokerage data	Retail investors	Alpha, raw return	Home Bias (3.2) → N/A	Based on gross returns, individual investors have an average skill of approximately -7.5% p.a. 89% of individual investors exhibit negative skill ($\alpha \leq 0$) when measured on a gross basis and 91% when considering returns net of costs and expenses

Table 1 (continued)

Study	Sample period	Country	Data set	Target group	(1)	(2)	Key findings
(Faruquee et al. 2004)	2004	Multiple	Survey of international portfolio holdings	Indices	Raw return	Home bias (3.5) → Negative	International portfolio holdings are determined by market size, transaction costs, and information costs. The estimation results also support explanatory return-chasing behavior and portfolio diversification as implied by the international CAPM. These results suggest that international investing behavior is determined by multiple factors, which helps explain why single-factor models are inadequate in solving the home bias puzzle Financial market size and information asymmetry are major determinants of international portfolio choice and home bias

Table 2 Overview of identified behavioral biases: (1) used in the number of studies and (2) identified total number of different measurements for the respective bias

Bias factor	Description	Proxy for	(1)	(2)	Effect
Disposition effect	Tendency to sell winners too early and hold losers too long	Loss aversion	13	6	Negative
Under-diversification	Tendency to hold few or concentrated positions	Overconfidence	12	4	Negative
Home bias	Tendency to select stocks with headquarters in the investor's home country	Familiarity bias	6	5	Positive and negative
Local bias	Tendency to select stocks with headquarters close to the investor's geographical location	Familiarity bias	6	2	Positive and negative
Lottery stock preference	Tendency to select stocks with lottery-like features (low price, volatile, and high recent return)	Gambling preference	8	4	Negative
Trend chasing	Tendency to chase assets with high recent returns	Extrapolation bias	4	1	Positive and negative
Leading turnover share	Tendency to systematically trade before other investors	Informed trading	1	1	Negative
Overtrading	Tendency to trade frequently	Overconfidence	8	1	Positive and negative
Overconfidence	Tendency to trade frequently but unsuccessfully	Overestimate one's knowledge or skill	2	1	Negative
Trade clustering	Tendency to select investments individually instead of considering the broad impact on the portfolio	Narrow framing	3	2	Positive and negative
Inattention to news	Tendency to (not) trade a particular individual stock around a news event	Uninformed trading	1	2	Negative

Table 3 Overview of measurements: (1) theoretical range and (2) used in the number of studies. (Disposition effect 1.x, under-diversification 2.x, home bias 3.x, local bias 4.x lottery stock preference 5.x, trend chasing 6.x, leading turnover share 7.x, overtrading 8.x, overconfidence 9.x, trade clustering 10.x, and inattention to news 11.x)

#	Operationalization of behavioral bias factors	(1)	(2)
1.1	$\text{Disposition Effect}_{it} = \frac{\text{Realized Gains} - \text{Realized Losses}}{\text{Realized Gains} + \text{Realized Losses}}$	-1 - 1	1
1.2	$\text{Disposition Effect}_{it} = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Unrealized Gains}} - \frac{\text{Realized Losses}}{\text{Realized Losses} + \text{Unrealized Losses}}$	-1 - 1	10
1.3	$\text{Disposition Effect}_{it} = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Unrealized Gains}} - \frac{\text{Realized Losses}}{\text{Realized Losses} + \text{Unrealized Losses}}$	0 - +∞	2
1.4	$\text{Disposition Effect}_{it} = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Realized Losses}} - \frac{\text{Paper Gains}}{\text{Paper Gains} + \text{Paper Losses}}$	-∞ - +∞	1
1.5	$\text{Sale}_{ijt} = b_0 + b_1 \text{Gain}_{ijt} + \epsilon_{ijt}$	-∞ - +∞	1
1.6	Cox Regression (Cox 1972)	-∞ - +∞	2
2.1	$\text{Number of Stocks} = N$	1 - +∞	8
2.2	$\text{Herfindahl Index} = \sum_{i=1}^N \text{weight}_i^2$	1 -> 0	4
2.3	$\text{Normalized Portfolio Variance} = \frac{\sigma^2}{\sigma}$	0 - 1	3
2.4	$\text{Return Loss} = \mu_b * \omega_h * \beta_h * \frac{\text{Sharpe Ratio}_b - \text{Sharpe Ratio}_h}{\text{Sharpe Ratio}_b}$	-∞ - +∞	2
3.1	$\text{Home Bias}_i = \frac{\text{Share of Domestic Equities}}{\text{Share of Domestic Equities}^{\text{Benchmark}}}$	0 - 1	1
3.2	$\text{Home Bias}_i = \text{Share of Domestic Equities}$	0 - 1	2
3.3	$\text{Home Bias}_i = \text{Share of Foreign Equities}$	0 - 1	1
3.4	$\text{Home Bias}_i = 1 - \frac{\text{Share of Foreign Equities}}{\text{Share of Foreign Equities}^{\text{Benchmark}}}$	0 - 1	1
3.5	$\text{Home Bias}_i = \text{Share of Domestic Equities} - \text{Share of Equities}^{\text{Benchmark}}$	-1 - 1	1
4.1	$\text{Average Distance}_{it} = \sum_{j=1}^N (\text{distance}_{ij} * \text{weight}_{ij})$	0 - +∞	3
4.2	$\text{Local Bias}_i = \text{Share of Local Equities}$	0 - 1	5
5.1	$\text{Lottery Preference}_{it} = \text{Share of Lottery Stocks}$	0 - 1	7
5.2	$\text{Lottery Preference}_{it} = \frac{\text{Share of Lottery Stocks} - \text{Share of Lottery Stocks}^{\text{Benchmark}}}{\text{Share of Lottery Stocks}^{\text{Benchmark}}}$	0 - 1	2

Table 3 (continued)

#	Operationalization of behavioral bias factors	(1)	(2)
5.3	Lottery Preference _{it} = $\frac{\text{Share of Lottery Stocks}}{\text{Share of Lottery Stock Benchmark}}$	0–1	1
5.4	Lottery Preference _{it} = Share of Lottery Stocks Purchases	0–1	1
6.1	Average trend before all trades (k) = $\sum_{j=1}^{N_i} r(i, j, k)$	$-\infty$ – $+\infty$	5
7.1	Leading Turnover Share _{it} = $\frac{\text{Leading Turnover}}{\text{Total Turnover}}$	0–1	1
8.1	Average Portfolio Turnover = $\frac{1}{2} \cdot \min \left(\frac{\text{Purchase Volume}_{t-1}}{\text{Portfolio Volume}_t} \right) + \frac{1}{2} \cdot \min \left(\frac{\text{Sale Volume}_{t-1}}{\text{Portfolio Volume}_t} \right)$	0– $+\infty$	7
9.1	Overconfidence Dummy Variable equal to one for investors in the highest portfolio turnover quintile and lowest per formance quintile for their individual common stock trading and zero otherwise	0–1	2
10.1	Trade Clustering _{it} = $1 - \frac{\text{Number of trading days}}{\text{Number of trades}}$	0–1	2
10.2	Trade Clustering _{it} = $1 - \frac{\text{Number of trades}}{\text{Number of trading days}}$	$-\infty$ –0	1
11.1	Inattention to Earning News = $1 - (\text{number of investor trades around the event}) / (\text{total number of investor trades})$	0–1	1
11.2	Inattention to Macroeconomic News = $1 - (\text{number of investor trades around the event}) / (\text{total number of investor trades})$	0–1	1

Table 4 List of recommended behavioral bias factors and measurements for future research (see Table 3 for the respective formulas)

Behavioral bias factor	Formula(s)
Disposition effect (DE)	1.2
Under-diversification (UD)	2.1, 2.2, 2.3
Home bias (HB)	3.2
Local bias (LB)	4.2
Lottery stock preference (LSP)	5.1
Trend chasing (TCH)	6.1
Overtrading (OT)	8.1
Trade clustering (TCL)	10.1

3.3.1.1 Biases related to portfolio composition Twenty studies examined biases that influence the composition and structure of investment portfolios, such as under-diversification, home, and local bias. The under-diversification factor, frequently driven by overconfidence (Ivković and Weisbenner 2005; Leković, 2020), results in investors holding concentrated investment portfolios, which is measured by the number of stocks held (number of stocks), the summed squared weight of all portfolio positions (Herfindahl index), or the squared variance of the portfolio divided by the squared average variance of the individual stocks in the portfolio (normalized portfolio variance). The tendency to hold concentrated portfolios can further be induced by the familiarity bias, for example, by preferring companies from one's home country or nearby locations, which is operationalized by computing the ratio between the volume of home or local stocks and the total portfolio volume (Grinblatt and Keloharju 2001; Lovric et al. 2010).

3.3.1.2 Biases related to the decision-making process Another 17 studies examined biases that impact investors' trading decisions and frequency. Overtrading arises from overconfidence (Barber and Odean 1998; Graham et al. 2009), causing frequent trading and thus an increased purchase and sales transaction volumes (average portfolio turnover) that may lead to suboptimal performance. Leading turnover share and inattention to news indicate an inclination to informed trading, measured by executed trades ahead of other investors or around news events (Bailey et al. 2011; Weber et al. 2014). Trade clustering, calculated by the number of trading days by the number of trades, proxies for the narrow framing bias, wherein investors trading on multiple days tend to make isolated trading decisions, i.e., not considering their broader portfolio impact (Kumar and Lim 2008). Lastly, the disposition effect examines if investors hold on to their losing investment due to loss aversion (Kahneman and Tversky 1979; Odean 1998), which can be observed by examining the proportion of realized and unrealized losses to gains.

3.3.1.3 Biases related to stock picking Investors exposed to lottery stock preference and trend chasing tend to buy high-risk stocks with speculative attributes, e.g., high volatility, high recent return, and low price (Bali et al. 2011, 2017, 2021; Dhar and Kumar 2001). While trend chasing only considers newly purchased

transactions with speculative attributes, lottery stock picking measures the overall ratio of speculative stocks and the total portfolio volume. Ten studies examined these biases (Table 2), which collectively underscore the cognitive influences on individual stock selection, ranging from sensation-seeking behaviors to the overconfidence-driven preference for trending assets or an inflated perception of one's forecasting acumen.

3.3.2 Operational differences to measure behavioral biases

Twenty-nine measurements were identified for the eleven bias factors and are presented in Table 3. The differences in measures vary with the required data input, the computational arrangement of variables, and their theoretical range.

3.3.2.1 Different data requirements Several data sources are required to measure the identified bias factors. All 29 measurements need portfolio trading data, at least either portfolio holdings or transaction data. Additionally, bias factors such as home and local bias require information about the assets and the investor, i.e., the country or location of the asset's headquarters and the investor's geographical position. For lottery stock preference and trend chasing, information about an asset's historical performance is required for its measurements. Bias factors, that proxy for informed trading, require public news data, e.g., relevant macroeconomic news related to the respective portfolio holdings.

3.3.2.2 Different mathematical computations Eight of 11 bias factors (disposition effect, home bias, trend chasing, leading turnover share, average portfolio turnover, overconfidence, trade clustering, and inattention to news) differ only because of their measurement techniques, e.g., subtracting instead of dividing the share of domestic holdings from overall portfolio holdings for the home bias (formulas 3.1 and 3.5 in Table 3). The remaining three bias factors (under-diversification, local bias, and lottery stock preference) differ in operationalization (required input variables). The under-diversification measures either consider the number of stocks (2.1), consider the weights of portfolio positions (2.2), consider the portfolio variances (2.3), or consider the beta-induced return loss (2.4). One measurement (4.1) of the local bias calculates the absolute distance between the asset's headquarters and the investor. In contrast, the other formula (4.2) measures the share of local equities, which is determined by a threshold distance in the portfolio. For lottery stock preference, three of four measures consider the share of lottery stocks in portfolio holdings, while formula 5.4 only focuses on the share of lottery stock purchases.

3.3.2.3 Different theoretical ranges Fifteen of 29 measurements indicate a theoretical range from 0 to 1, 10 measures have at least a one-sided infinite range, and nine measures can obtain negative values. These differences occur across the 11 bias factors and in measures within one bias factor, e.g., the six disposition effect measures have three different theoretical ranges.

3.3.3 Performance measures and effects of behavioral biases

Four techniques to measure portfolio performance were identified in the reviewed studies and are presented in Table 1. Seventeen of the 34 studies used factor models, including an alpha component (Carhart 1997; Fama and French 1993; Jensen 1968), which is used to determine the abnormal return of a security or portfolio of securities over the theoretical expected return. Further, ten studies used Sharpe ratios (Sharpe 1964), another ten used raw returns, and five used excess returns to a chosen benchmark. Six of the 34 reviewed studies did not provide a performance measure as the focus of these studies was, e.g., to examine the link between specific bias factors and investor characteristics (Dhar and Zhu 2006) and not performance impact.

According to Table 2, the included studies showed that most of the biases are costly. However, some investors seem to expose themselves to biases, e.g., consciously highly concentrate their portfolios (under-diversification, local bias, and home bias) and earn abnormal returns (Coval and Moskowitz 2001; Ivković et al. 2008; Ivković and Weisbenner 2005; Seasholes and Zhu 2010; Von Nitzsch and Stotz 2005; Weber et al. 2014). Another exception is trend chasing, as Dhar and Kumar 2001 show that contrarian investors may earn higher returns by selling instead of holding winners.

4 Discussion

4.1 Behavioral bias factors and their measurements

The systematic review highlights the importance and impact of behavioral bias factors on portfolio performance to raise awareness of costly behaviors to protect the retail investor's financial health. The core findings of this review are that the 11 bias factors have been proven economically significant in several settings. However, mixed results (effects) are also presented in Table 1, especially regarding the concentration of portfolios and stock-picking skills of investors, which require further examination.

The review indicates a reliance on the USA-based research and data scarcity in general (Table 1). Most studies were conducted in the USA ($n=22$) and used brokerage trading data ($n=15$). However, 11 of these 15 studies used the same data set from Odean (1998). All other studies constructed or obtained their own data sets (no overlaps), which means that despite the scarce data availability, researchers seem to keep their data set private. While the USA focus may be explained by the high willingness of the USA population to invest in the capital market, data scarcity is a well-known problem that hinders further investigation of bias factors to derive countermeasures against these costly behaviors. Solving this problem should be endorsed by brokerage firms as their customers, the investors, are more likely to stop trading after realizing their ability to trade is low (Seru et al. 2010).

Several cognitive biases induce costly investment behaviors for investors, such that investors deviate from the standard Modern Portfolio Theory (Markowitz 1952). The identified bias factors suggest that these deviations are caused by

investors' insufficient decision-making process and inability to pick and manage their portfolios.

Studies examining bias factors related to portfolio composition—home bias, local bias, and under-diversification—indicate conflicting impacts on investors' portfolio performance. At the same time, several studies report negative returns (Bailey et al. 2011; Calvet et al. 2006; Faruquee et al. 2004; Grinblatt et al. 2011; Han and Kumar 2013), while some studies find conflicting or positive returns associated with home and local bias (Coval and Moskowitz 2001; Goetzmann and Kumar 2008; Ivković et al. 2008; Ivković and Weisbenner 2005; Seasholes and Zhu 2010; Von Nitzsch and Stotz 2005). Positive returns for home bias were found only for samples from the USA and no other country, which may be explained by its market capitalization and developed capital market. Examining the geographically even more detailed local bias, Ivković et al. (2008) found that the average household within their USA sample generates an additional return of 3.7% per year from its local holdings relative to its non-local holdings, suggesting that local investors can exploit local information. This is especially true for stocks not in the S&P500 index. Their results are not driven by specialization in a particular industry, inside information, broad market timing, repeated trades in a particular stock, or regional differences across investors. Instead, the results reflect that wealthy households who concentrate their holdings on a few stocks tend to be able to identify superior stock picks. However, these excess returns come with larger risks and lower sharp ratios. Another reason for local bias may be discounted rates for employees to buy company stocks.

Among others, Calvet et al. (2006) reported that Swedish investors lose up to 10% return p.a. due to holding undiversified portfolios. They add that households outperform the domestic benchmark via international diversification or fund investing. Grinblatt et al. (2011) found that higher IQ leads to a higher Sharpe ratio (mainly because of lower volatility), more stocks held, and a higher probability for a fund to be held and, thus, more diversification. Among active (highest turnover quintile) investors, less diversified investors have a higher return and alpha than better-diversified investors (Goetzmann and Kumar 2008). This evidence aligns with the mentioned small, active group of under-diversified investors who might be skilled in exhibiting home and local bias.

Further studies measure bias factors related to the decision-making process—disposition effect, overtrading, overconfidence, trade clustering, leading turnover share, and inattention to news—and are associated with a mostly negative impact on portfolio performance (Table 2). The disposition effect is this review's most examined bias factor ($n = 13$). Investors that exhibit the disposition effect underperform investors with no disposition effect by 2.35% p.a.. For winners that are sold, the average excess return over the following year is 3.4% more than for losers that are not sold, suggesting that investors should rather hold on to winners and sell losers (Odean 1998).

This finding is in line with the results of overtrading that purchases of an investor underperform their sales by an average return of 3.31% p.a. (Odean 1999). While men indicate a higher exposure to overtrading (6.4% annual turnover) compared to women (4.4% annual turnover), both men and women achieve a lower return by trading (Barber and Odean 1998), which costs them 6.8% p.a. relative to the returns

earned by low turnover households (Barber and Odean 2000). These investors in the highest portfolio turnover and lowest performance quintile, i.e., those who trade the most but attain the worst performance, are labeled overconfident (Bailey et al. 2011; Goetzmann und Kumar 2008). As trading is detrimental, these findings suggest that investors should stick to the buy-and-hold strategy, which should eliminate the disposition effect, overtrading and consequently overconfidence. Also, wealthier individuals and individuals employed in professional financial occupations exhibit a lower disposition effect and trading frequency (Dhar and Zhu 2006). In an experiment, Fischbacher et al. (2017) found that automatic selling devices helped investors to increase the proportion of losers realized.

Another costly bias-induced behavior is trade clustering. Investors with the highest (and thus the broadest framing) and those investors with the lowest trade clustering (and hence the narrowest framing) differ by 1.6% (Kumar and Lim 2008) and 2.1% (Bailey et al. 2011) return performance p.a.. These two studies use slightly different measures 10.1 and 10.2 which explain the given delta of 0.5% p.a. in the performance impact. Contrary to these findings, Weber et al. (2014) found that the average narrow-framed investor earns 2.12% p.a. more than the broader-framed. However, suppose an investor executes the same number of trades in fewer days, e.g., ten trades on one single day instead of two trades on 5 consecutive days. In that case, he should be broader-framed (instead of narrower) and thus make decisions more holistically, which should be more profitable in the long run. Lastly, the results for leading turnover share (Weber et al. 2014) and inattention to news (Bailey et al. 2011) hurt return, meaning that investors tend to time their buys and sales poorly. Better timing of investments might be possible by the cost averaging strategy or by constant acquisition of information and thus trading more informed.

In this review, ten studies included bias factors related to stock-picking abilities—lottery stock preference and trend chasing—which negatively impact portfolio performance. The investors' risk-seeking behavior induces a preference to buy lottery stocks, which are characterized by abnormal recent returns, low prices, and increased volatility and hurt the investor by 6.2% (Kumar 2009) or 7.2% (Han and Kumar 2013) performance reduction p.a.. These findings are consistent with studies focusing on analyzing individual lottery stocks and their performance (Bali et al. 2011, 2017, 2021; Bergsma and Tayal 2019). Lottery stocks represent 1.25% of the total stock market capitalization. However, their total number represents about 13% of the market, so retail investors should be even more cautious because of their disproportionate presence (Kumar 2009). Consistent with the evidence that lottery demand is attributable to individual, not institutional, investors, the beta anomaly is concentrated among stocks that have low institutional ownership (Bali et al. 2021). Having roughly double the standard deviation compared to non-lottery stocks, these stocks are associated with high-risk investments (Kumar 2009). Further, most lottery stocks are primarily present in the energy, mining, financial services, biotechnology, and technology sectors and are less present in utilities, consumer goods, and restaurants (Kumar 2009).

Similar to lottery stock characteristics, the measure for trend chasing uses the average recent k -day returns of stocks to measure trend chasing behavior. Dhar and Kumar (2001) found a negative portfolio impact of 4.4% p.a. for momentum retail

investors, while contrarian retail investors, who buy against the trend, seem to earn abnormal returns of 7% p.a. in comparison. Sirri and Tufano (1998) examined trend chasing for mutual funds and found that buyers of equity funds disproportionately stick to high-performing funds while failing to exit lower-performing funds at the same rate. High performance is most salient for funds with higher marketing efforts, as measured by higher fees. Flows are directly related to the size of the fund's complex, and the current media attention received by the fund, which lowers consumers' search costs.

4.2 Comparability of bias factors

In this review, 28 of 34 studies provided a performance measure to compare biases based on their impact on returns. The most frequent performance measures were factor models, including an alpha component (alpha measures), Sharpe ratio, excess return, and raw return, which differ in interpretability. Raw returns provide an unmodified view of performance. However, not considering a benchmark, raw data complicate evaluating whether the achieved results were good or bad depending on the settings, e.g., sample and time.

Excess returns consider a benchmark, as they measure the respective over- or underperformance (excess). But studies choose different benchmarks and, for example, measure excess return compared to the market portfolio (e.g., Goetzmann und Kumar 2008) or between quantiles of retail investors, e.g., quantiles determined by their exposure to a bias factor (e.g., Odean 1998; Kumar und Lim 2008). This means that excess return only enables a comparison of results across studies if the samples are the same or within one sample between subsets of investors.

The Sharpe ratio quantifies risk-adjusted returns, which enables the comparison of investments' performance relative to their risk levels and thus helps to raise awareness for retail investors. However, its reliance on assumptions of normal distribution and a single risk measure (variance) may limit its accuracy and applicability in capturing the intricacies of diverse investment scenarios.

The advantage of using factor models including an alpha measure, e.g., the Fama–French model, for comparing different research studies lies in its wide acceptance in studies and accessibility of its historical data. French provides access to historical data by maintaining a website that provides historical data related to several variations of factor models, allowing cross-study comparison. Still, interpreting Fama–French alpha values can be complex, as these models' returns are attributed to several model factors, requiring careful consideration and contextual analysis when comparing researchers' regression analyses.

5 Conclusion

This paper presents 11 behavioral bias factors (Table 2) and 29 corresponding measurements (Table 3). While some bias factors are well examined, e.g., disposition effect and under-diversification, more recently developed factors need further

investigation, e.g., leading turnover share and inattention to news. Further, the identified bias factors differed in the required data input and measurement techniques. With these differences, the complexity of the measures varied from, e.g., simply counting the number of stocks to conducting a regression analysis to determine a single bias factor (Table 3). In addition, different theoretical ranges of measures, including differences within one bias factor, complicated the comparison across studies. Regarding the effect on return, four performance measures were presented, and factor models including an alpha measure, e.g., the alpha of the Fama–French three-factor model, were found most helpful to allow for cross-validation across multiple studies because it offers a publicly available factor model as a benchmark, thus easing comparability.

Overall, the bias-induced behaviors of under-diversification and lottery stock preference were found to be the most hurtful, while some investors with a home or local bias seem to exploit superior information and earn an excess return compared to the market portfolio.

As the provided list of measurements is already extensive (Table 3), it provides a great opportunity to improve the design of portfolio analytic tools and include behavioral bias factors in a portfolio overview where returns are attributed to the respective bias factor. Therefore, with an application-oriented focus, further investigations should focus on two things: First, they should focus on bias factors that are easy to calculate to enable recalculating these for further research and financial tool providers, and second, they should focus on bias factors that are simple to follow to ensure their understandability for the retail investor. It is further recommended to include the most researched bias factors (Table 2) in a factor model, which are also the most detrimental to portfolio performance, as well as to include the most frequently used and least complex measures (Table 3), which results in the primary inclusion of the eight behavioral bias factors and their measures presented in the following Table 4.

These behavioral bias factors should be used to explain the idiosyncratic component (alpha) of the factor models described in Sect. 1, resulting in the following adjustment of the formula (6):

$$\alpha_j = \beta_1 * DE_1 + \beta_2 * UD_2 + \beta_3 * HB_3 + \beta_4 * LB_4 + \beta_5 * LSP_5 + \beta_6 * TCH_6 + \beta_7 * OT_7 + \beta_8 * TCL_8 + \varepsilon \quad (7)$$

Instead of deriving further sophisticated measures for these biases, future research should focus on the recommended existing list of bias factors and measurements (Table 4) and examine if all provided behavioral bias factors in (7) add value in explaining the abnormal return of retail investors. A reduced scope of factors should further enhance the investors' understanding of their exposure to behavioral biases, thus increasing the chance of mitigating these costly behaviors. In addition, future research should further examine normalization methods, as the examined measures in this paper showed differences in theoretical ranges, which may significantly impact multivariate analysis models.

Eventually, it should be a common goal for policymakers and brokerage firms to design a financial tool, e.g., a behavioral performance return attribution overview,

to help investors protect their investments by raising awareness of their costly behaviors.

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